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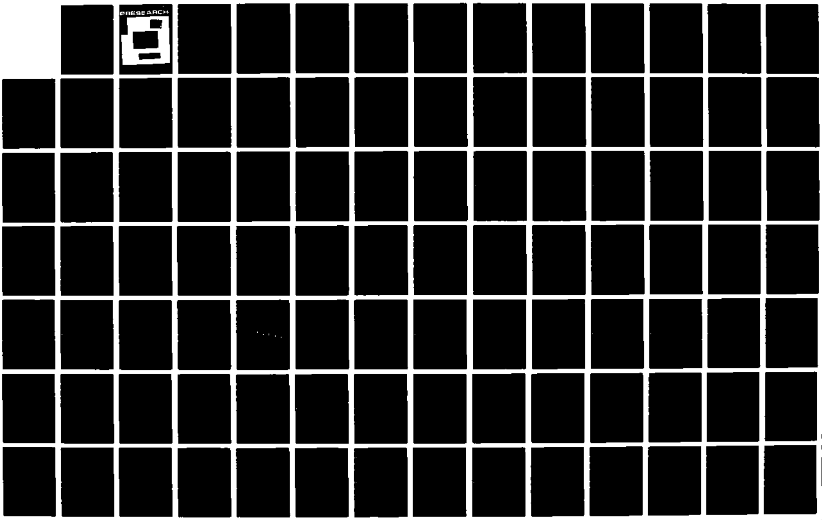

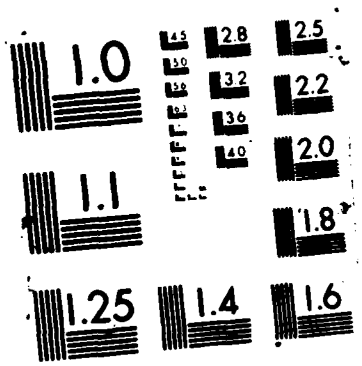
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Transient Classifier Systems and Man-Machine Interface Research

by

Dr. Robert Sax and Richard Kram

31 August 1987

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Psychophysical experiments on human observers showed that transient detection and classification performance were highly independent and very sensitive to signal-to-noise ratios. The transients were recognized rapidly. Transient specific syntax was a strong determinant of performance. The automatic classification algorithm demonstrated use of syntactic and semantic state variable feature-space representations to perform computationally efficient classificiation of transient patterns (50 x real-time in FORTRAN) and large-scale reduction of data (500 to 1). Algorithm recognized many singular and correclated transient events. An unexpected result was recognition and modal separation of mixed-mode tonal signals as correlated transients in the time domain.

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TRANSIENT CLASSIFIER SYSTEMS AND MAN-MACHINE INTERFACE RESEARCH SBIR PHASE I PROJECT SUMMARY

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1. **Purpose**. The purpose of Presearch's Phase I research was to investigate human classification performance and the underlying psychophysical models of perception and cognition. The research was directed toward the Navy's need for effective acoustic transient classifier systems for advanced ASW programs; where effectiveness must be measured in speed, accuracy, and operability. This basic classification research is also applicable to fields such as real-time classification of radar signals, seismic processing, and monitoring vibrations for incipient failures and loose parts at nuclear power plants.

2. **Description of Work**. The work performed in Phase 1 consisted of a pilot psychophysical experiment and automatic classification algorithm research on the NRL Cray Computer. Our research approach is to integrate psychophysical perceptual and cognitive models of human classification into the design of intelligent adaptive transient detector/classifiers. Central to the research is the transformation of continuously sampled acoustic data into an efficient representation of replicable finite patterns. This Asynchronous Syntactic Pattern (ASP) sensor concept is used to reduce computer processing/storage requirements and to simplify human classification tasks.

3. **Results**. The results of the experiment showed that transient detection and classification performance are highly independent, and both are very sensitive to signal-to-noise ratio (SNR). Unknown transients were recognized rapidly; however, performance at low SNR was not comparable to that against known transients. Transient specific syntax proved to be an even stronger determinant of performance than the known vs. unknown condition. Novice performance in detecting a target by its transient emissions was comparable to theoretical best current broadband techniques. Experienced sonar operators outperformed the novices by 12 dB.

The automatic classification algorithm research demonstrated use of syntactic and semantic state variable feature-space representations to perform computationally efficient classification of transient patterns (50 times real-time in FORTRAN) and large-scale reduction of data (500:1). The algorithm recognized many singular and correlated transient events. An unexpected and exciting result was recognition and modal separation of mixed mode tonal signals as correlated transients in the time domain.

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1.0 EXECUTIVE SUMMARY

1.1 BACKGROUND

Presearch has performed basic research on the detection of underwater acoustic transients under Internal Research and Development for the past several years. The research focused on a time domain based Automatic Disturbance Monitor (ADM) capable of performing feature recognition of replicable transient events. This previous research, when applied to certain types of actual transient data, demonstrated some inherent advantages over more conventional spectral-domain approaches. This included more robust and sensitive detection of transients of variable duration, shape, and bandwidth. Presearch has a strong background in man-machine interface (MMI) design of displays, controls, and interactive decision aids. In the present research we are combining these capabilities and expanding our basic research of automatic algorithms and MMI towards an integrated workstation concept for improving transient classification.

1.2 PURPOSE

Presearch's research is focused on the underlying psychophysical models of perception and cognition and their application to the man-machine interaction required to optimize detection and human classification performance. Realistic operational context was used wherever it did not impose unreasonable constraints on the basic research.

1.3 APPROACH

Our research approach is to integrate psychophysical perceptual and cognitive models of human classification into intelligent detection/classifier applications. Central to the research is the idea of immediately transforming continuous sampled acoustic data into finite patterns by means of an Asynchronous Syntactic Pattern (ASP) sensor. The idea of autonomous representation of finite patterns from a data stream reduces storage requirements and simplifies classification responses of a human operator. Syntactic and semantic state variables constitute the central parameters of the asynchronous interface.

1.4 DESCRIPTION OF WORK

The work includes a psychophysical experiment and automatic algorithm research. The psychophysical experiment was performed at the Catholic University Human Performance Laboratory. Its purpose is to demonstrate a testbed for comparing alternative detection/classification algorithms and MMI in terms of the efficiency and reliability of decision performance. Performance is measured by receiver operating characteristics (ROC), reaction time, and learning curves. Specific objectives are: (1) assess the impact of signal-to-noise ratio (SNR) on cognitive models of transient classification, (2) establish performance benchmarks for comparing alternative methodologies, and (3) evaluate the impact on performance of noise on detection and classification of known and unknown transient signal patterns.

The automatic classification algorithm research analyzed unclassified transient acoustic events. The purpose of the research was to apply psychophysical models in automatic transient data pattern analysis, detection, and classification concepts. The goal was automatic feature representation of transients applied as a self-learning algorithm for identifying the feature pattern of correlated transients, and a binary state variable syntax algorithm for recognizing the syntactic pattern of these transient features. The calculations were performed on the Cray Computer at the Naval Research Laboratory.

1.5 RESULTS OF RESEARCH

1.5.1 Psychophysical Experiment

Preliminary analysis of the pilot experiment has produced the following six significant results regarding detection and classification of underwater transients:

1. Transient detection and classification performance is related to propagation distance and SNR.

2. Novices detect and classify unknown transients. This implies internal representation and recognition of pure noise backgrounds.

3. Information feedback after classification resulted in better performance at low SNR.

4. Variance in performance from transient to transient, the specific structure (syntax) effect, was much stronger than variance between known vs. unknown groups.

5. Detection performance with acoustic transients by novices was comparable to that expected of broadband signatures; performance of experienced sonar operators was 12 dB better.

6. Detection and classification decisions are interrelated differently for high and low SNR transient signals.

1.5.2 Automatic Detection/Classification Experiment

The result of the automatic classification experiment indicated that signals could be precisely correlated by replicative feature patterns or by matching bit mapped syntax. Information about sources could be ascertained by automatically sensing the features of replicated pulses. The following is a brief description of the feature classification hierarchy utilized for the preliminary feasibility analysis:

1. At the top of the feature classification hierarchy are entities: Leading Edges of long complex episodes; narrowband Pulsed Carriers; and broadband Pulses.

2. The second level is described by a set of feature patterns dependent on pulse shape, dominant frequency, and frequency shift characteristic.

3. The third level is a bit-mapped syntactic time-ordered pattern of a specific feature or feature pattern.

The following points summarize the results of testing the automatic classification algorithm:

1. Out of six long complex Leading Edge signals examined, two of them correlated, (a) by extremely precise feature attribute values at the first pulse of the wave train, and (b) by 100% bit matching of the syntax of energy excitations indicating a clear and confirmed replication of the complex event.

2. Numerous Pulsed Carriers were sensed. Most were apparently random perturbation of feature values as would be expected from chance occurrences in the random background. In two cases, in the one-minute sample of data which was analyzed, the same feature pattern was replicated many times; eight times in one case; twelve, in the other case. More work needs to be done to be certain as to whether the repeated features are due to chance, random multiple occurrences of a transient pulse, or periodic occurrences which were randomly modulated above the broadband background. The latter source would be due to constructive interference of overtones of different timbre from two different resonant sources, i.e., like a violin and oboe emitting nearly the same fundamental mode frequency, but each with its own unique set of harmonics. The effect could not be produced by feature detection and classification of white random data. The randomization of timbre peak occurrences may be due to the low S/N relative to the broadband background or due to the effect of sub-harmonics of finite amplitude sources.

3. The replicated pulse arrivals observed in the minute sample of broadband data were automatically sensed. Their time differential matrix was computed. Analysis of presumed timbre peaks as integer arrivals identified

them as due to possibly stable overtones; one with a timbre peak repetition time of 3.4693 msec; the other 3.0884 msec. These were sensed in the same overlapping time interval as distinguishable pulses identifiable by their characteristic feature value pattern. The analysis indicated that time peaks could be timed with a standard deviation of .2 to .4 msec.

4. Possible multipath arrivals (energy from a single source travelling along different paths) were identified with an apparent reflection coefficient as high as .95. These are of doubtful validity in that such effects were observed in random noise tests. More features would be required for reliable correlation of multipaths.

5. Source characteristics were extracted from broadband data at very low recognition differentials by identifying replicated feature patterns in real time. Only a few out of thousands of replications of a beat pattern need to be sensed in order to identify such sources and to identify their carrier frequency and pulse repetition rate.

6. Data sampled at 8000 Hz was processed with the automatic classification algorithm in nonoptimized FORTRAN code at 50 times real time on the NRL Cray Computer. Automatic feature classification reduced the storage requirement for data by a factor of 500.

Our Automatic Detection/Classification Experiment demonstrated the capability of finding sources of unknown transient waveforms in real time by automatically classifying entities, i.e., pulses and complex episodes of pulses. Also, by correlating replicable features of each entity and by correlating the time-ordered syntax feature patterns. The purpose of automatic detection/classification is real-time reduction of data to cues which support human classification and which trigger action based on recognition of important acoustic sources. It does this by extracting cues for immediate consideration; by removing known sources of causal uncertainty from the data stream; and by recognition of replicable patterns as unknown signals subject to possible semantic association.

1.6 POTENTIAL APPLICATIONS

This research effort is directly applicable to advanced submarine, surface ship, air, and surveillance antisubmarine warfare (ASW) combat system programs. Preliminary analyses of throughput on the Cray and the results of the psychophysical experiment indicate that current processing technology is sufficient to make major strides in: (a) reducing operator workload, (b) improving initial detection/classification performance, and (c) solving the ASW false alarm problem, including false alarms from transient detections and unclassified active and/or broadband contacts. Other signal processing applications include radar, seismic, and speech. An area of potential commercial application is incipient failure analysis of nuclear power plants and other error-critical physical processes.

1.7 CONTENTS

Section 2 contains the background and theoretical framework of our research. Section 3 describes the details of our Psychophysical Experiment. Section 4 describes our automatic classification research performed on the Cray Computer. Section 5 contains the references.

2.0 THEORETICAL FRAMEWORK

2.1 INTRODUCTION AND OVERVIEW

This section describes the background and theoretical framework for our transient classifier and man-machine interface (MMI) research.

Central to the research is the idea of immediately transforming continuous sampled acoustic data into finite patterns by means of an Asynchronous Syntactic Pattern (ASP) sensor. The idea of autonomous representation of finite patterns from a data stream reduces storage requirements and simplifies classification responses of a human operator. The ASP sensors transmit much less data; facilitating interactive classification decisions by a human operator and/or validating manual detection/classification decisions.

2.2 THE RESEARCH BACKGROUND OF AN AUTOMATIC DISTURBANCE MONITOR

Presearch sponsored 3 years of continuing research by Sax et al. (ref. 1, 2, 3, 4) on an Automatic Disturbance Monitor (ADM). This research pursued an episodic event automatic detection concept based on time domain pattern features of transient events. A Navy/Industry Cooperative Research and Development (NICRAD) agreement gave Presearch the opportunity to test our monitoring device on real acoustic transients.

In tests performed on acoustic transients, the largest transients occurred as episodes with intensities up to 50 dB above the average broadband background level. These episodes scaled with intensity. The smallest transient waveforms had highest frequency and bandwidth indicating the small spatial scale of the acoustic sources. By contrast, larger intensity transients, up to 50 dB larger than the smallest transients contained multiple bands of low bandwidth and low frequency. The rise time of leading edges and in some cases the pulses composing transient signals rose to full scale and in some cases decayed on a millisecond time scale. This time resolution requirement is the basis of our broadband time domain approach to processing signals from acoustic disturbances.

2.3 NOISE TESTS OF THE AUTOMATIC DISTURBANCE MONITOR

A simple model for transients as a time-domain detection entity is to presume the maximum episode is fixed at 50 dB above broadband background. It is assumed that the largest transient attenuates 10 dB in excess of the broadband background resonance emitted by the source. Assuming that largest episodes are detected at maximum distance from the source, the power excess of the largest transient impulse is at least 12 dB above the ocean noise background to maintain an acceptably low false alarm rate. With these conservative assumptions, detection of maximum episodes in the time domain is equivalent to sensing the resonant background source at -28 dB (50 dB-10 dB-12 dB) relative to ocean noise.

This idea was tested by adding gaussian noise to NICRAD test data with a result of -24 dB for a 50-dB episode. With a correction of 10 dB for absorption, -14 dB was obtained. This experiment's result deviated from the ideal of -28 dB expected. To acceptably control the false alarm rate in the experiment, a higher threshold of 14 dB was required. This accounts for 2.5 dB of the 14 dB discrepancy in detection. The use of a second difference operator applied to the data combined with nonlinear magnitude scaling of the transient episodes accounts for the rest.

Small episodes were always observed to have longer bandwidth than larger episodes, which were lower frequency and had much narrower bandwidth. The filter response of the ADM, which detected the second difference of transient data peaks, peaked at 6000 Hz and the response was down to -12.5 dB at the dominant 900 Hz frequency of the largest episode. Given this explanation, the results are consistent to within 1 dB of the above expectation. These results indicate no serious problem in designing a feasible detector of largest transient episodes. By removing the second difference operator, our experiment would have detected the source by instantaneous power emission at about -28 dB as expected.

2.4 THE ASYNCHRONOUS CLASSIFIER INTERFACE (ACI): A NEW ROLE FOR ADM

The filter of the ADM required a more appropriate design to optimize capture of largest episodes. In part, this problem was solved by designing the asynchonous sensor model tested on the Cray computer simply by eliminating the second difference prefiltering of input data, and by abandoning the concept of an energy detector. In abandoning energy threshold as a detection criteria, and substituting feature replication, we have the potential of increasing detection capability by as much as the 14 dB threshold requirement.

The ACI replaces energy detection by an asynchronous feature sensor. This sensor represents transients by a hierarchy of patterns. A syntactic representation of complex physical signals is well founded in psychophysics by Howard and Silverman (ref. 5), Howard and Ballas (ref. 6, 7), Howard (ref. 8) and Howard and O'Hare (ref. 9). The functions of feature sensors are to learn to form graphical and other possibly diagnostic pattern representations, to recognize known patterns in real time, and to recognize targeted patterns or pattern syntax which will point to files supporting sonar operator classification decisions. The ACI operating as a preprocessor aids classification by enhancing human perception and memory.

Analysis of ACI focused our research on ADM as an asynchronous pattern sensor in a man-machine interface workstation. ACI is an ADM model which provides automatic preprocessing background support of primarily interactive classification tasks. The automatic side of the interface is shown in Figure 2-1, taken from our Phase 1 ONR SBIR proposal. The overall architecture of the classifier interface is shown in Figure 2-2 from the same proposal. Our present theory of a classifier interface adheres to the proposed architecture, but the automatic background processing is slightly different.

In the revised approach, signal identification and discriminant encoding is hierarchical. At the highest level, a label is assigned to describe a transient entity, i.e., leading edge of a long wave train, or singular discrete impulse, etc. Next, the entity is described by a number of different features, such as wave shape, average frequency, frequency shift, bandwidth, modality, and other measurable characteristics. A certain type of entity is identified by replication of its encoded feature values. The dynamic pattern, formed by sequences of entity-features, defines the syntax of the complex transient disturbances of strings for feature attributes. A methodology of bit mapping syntactic data was described by Holland (ref. 10, 11) and others. The bit mapped state-variable input are "messages."

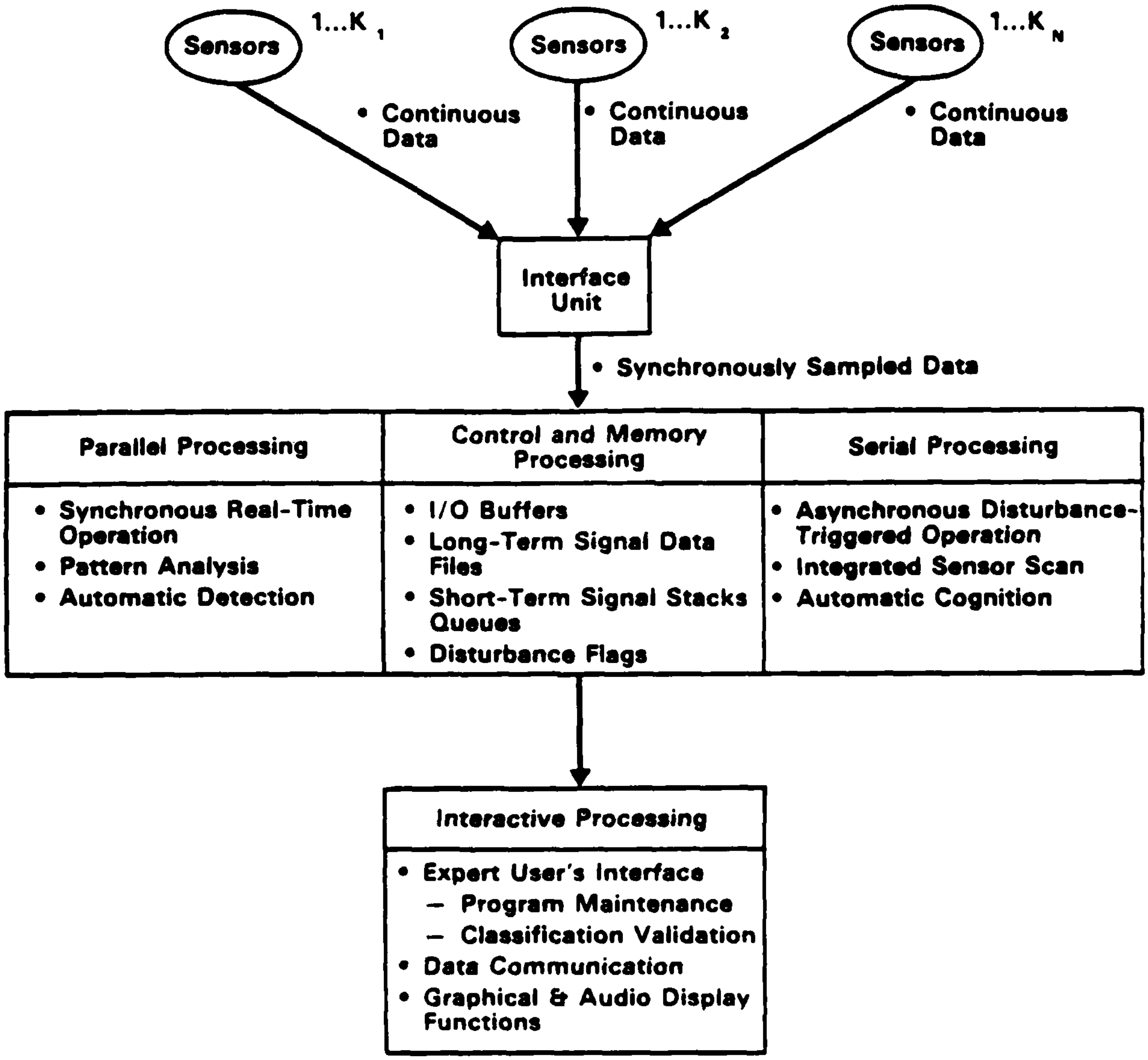

Figure 2-1. Automatic Disturbance Monitor (ADM) Architecture

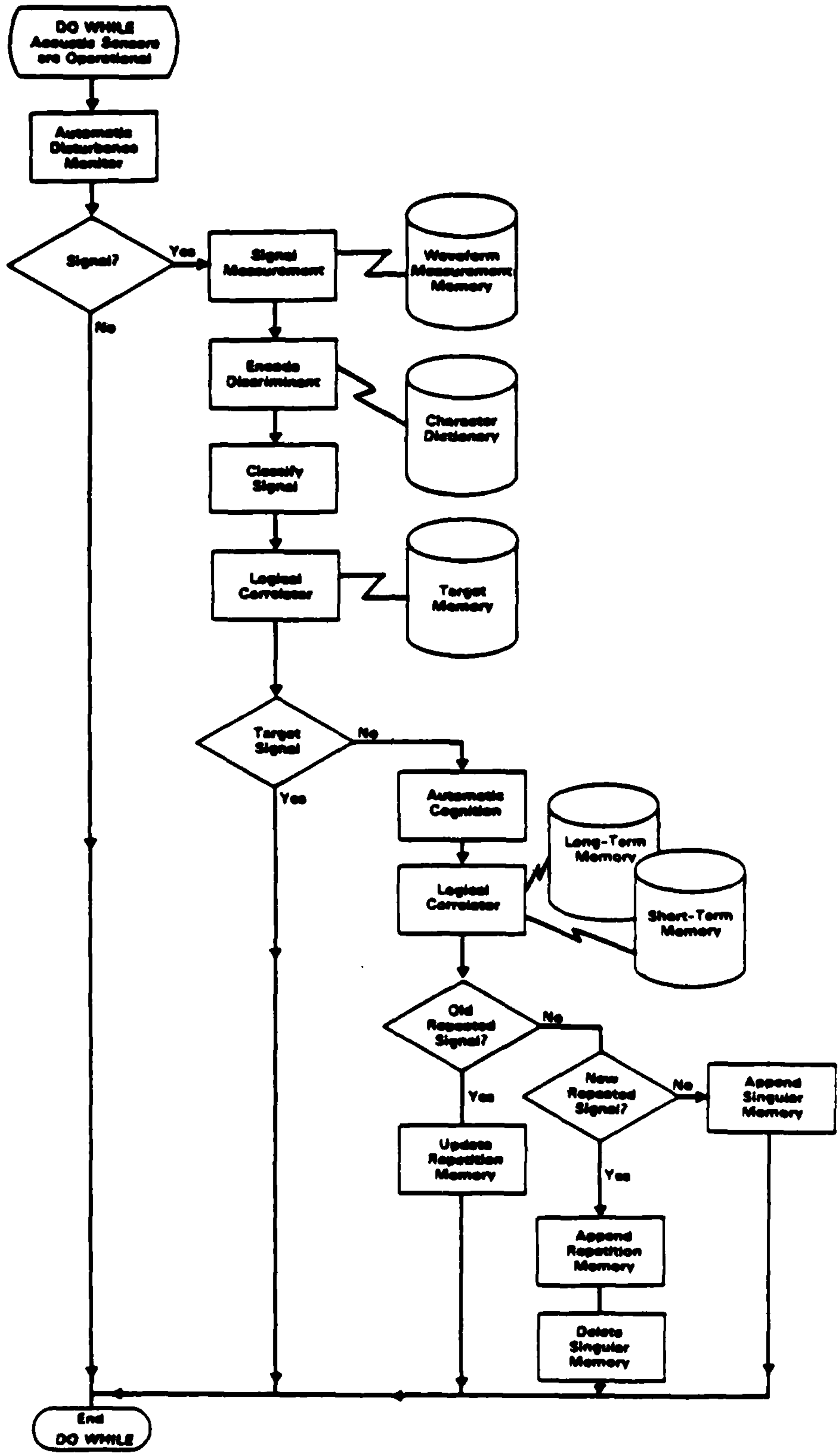

Figure 2-2. Man-Machine Interface (MMI) Background Processing System Functions

The Holland Classifier searches memory for a match between a new message and a stack of sorted patterns discerned from replication of old messages. Noisy messages with bit errors and weak messages with missing bits can be classified by fuzzy matches in a dictionary of sorted keys or by high covariances with a matrix of Holland Classifier Masks. A more recent approach to this bit-mapped classification approach is described by Frey (ref. 12). Holland Classifiers have been applied as knowledge models; for example, in predicting international events by Schrodt (ref. 13).

Our treatment of the problem of self-learning departs from the original model proposed for Phase 1. The former is shown in Figure 2-1 with untargeted messages referenced to a singular file. In the new model, features of singular signals are stored on large stacks in real-time program memory and are correlated with new messages in search of repetitions of feature patterns. Eventually, statistical descriptors of singularly uncorrelated signals are popped and pushed into a lower tier stack in search of longer time scale correlations. Replicated episodic signals with common features are set up as a temporary mask. The temporary mask's purpose is to initialize a new neural network connection by switching similar messages into the synapse until either a classification mask is formed or the connection is cut.

2.5 THE AUTOMATIC PROCESSING SIDE OF THE ACI

Encoding messages and recognizing known patterns has been discussed. Now the problem of transforming noisy messages and broken or partially defined patterns to known classification masks--automatic recall--must be considered. In addition to automatic recall; algorithms for self-learning of repeated patterns must be considered.

Neural network synapse models are used for two purposes: for induction or restoration of sufficiently well defined partial patterns, or to validate identification of noisy messages. A comprehensive description of neural network processing is given by Jorgensen and Matheus (ref. 14). Their neural network model of a synapse is the modification of a concept attributed to Hebb (ref. 15). It is remarkably analogous to a Dimus beamformer: a beamed array of correlated binary state-variable patterns of variable and unknown dimension.

A possible relation between pattern correlation and neural path activation is described by Kohonen (ref. 16). Rules cited by Rumelhart and Zipser (ref. 17) show ways of forming new connections and breaking off old connections as a basis for self-learning of new patterns. The progress we will report in our asynchronous sensor research on the Cray is limited to discriminant measurements and feature extraction algorithms. The building of a feature hierarchy and self-learning synapse models will be the goal of future research.

2.6 INTERFACE REQUIREMENTS OF ONLINE AUTOMATIC AND INTERACTIVE PROCESSING

The function of the classifier interface is to help a human operator make more accurate and faster classification of targeted sources. Tasks, associated with classification decisions, are partitioned between a background of automatic processing (shown in Figure 2-3) and a foreground of interactive processing (shown in Figure 2-4). The partitioning depends on the purpose of the classification. Two primary purposes exist: excitative classification of patterns possibly related to high priority targeted sources; and inhibitive classification of objects neither targeted for classification nor operationally

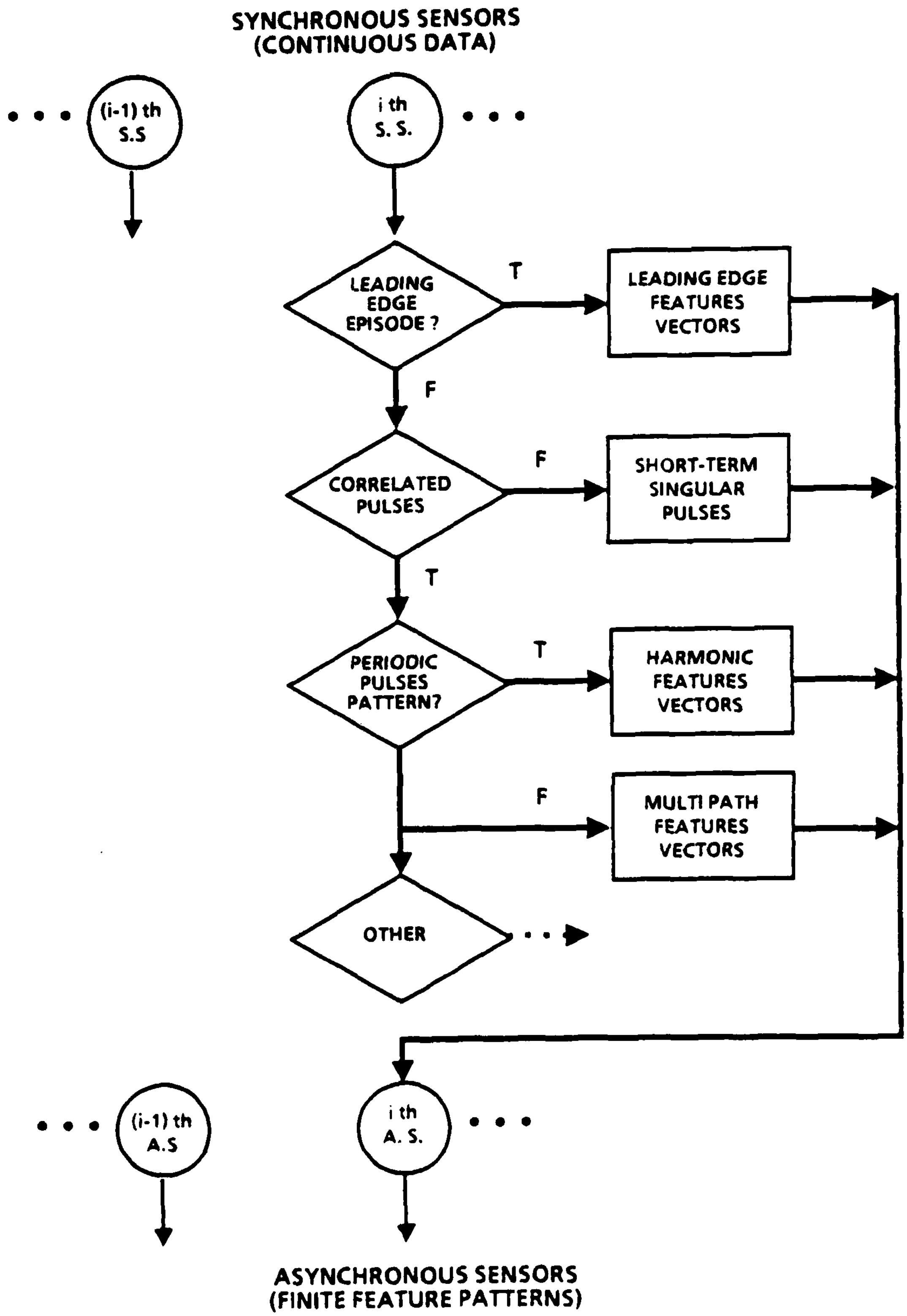

Figure 2-3. Automatic Feature Discriminator
(Background Processing Mode)

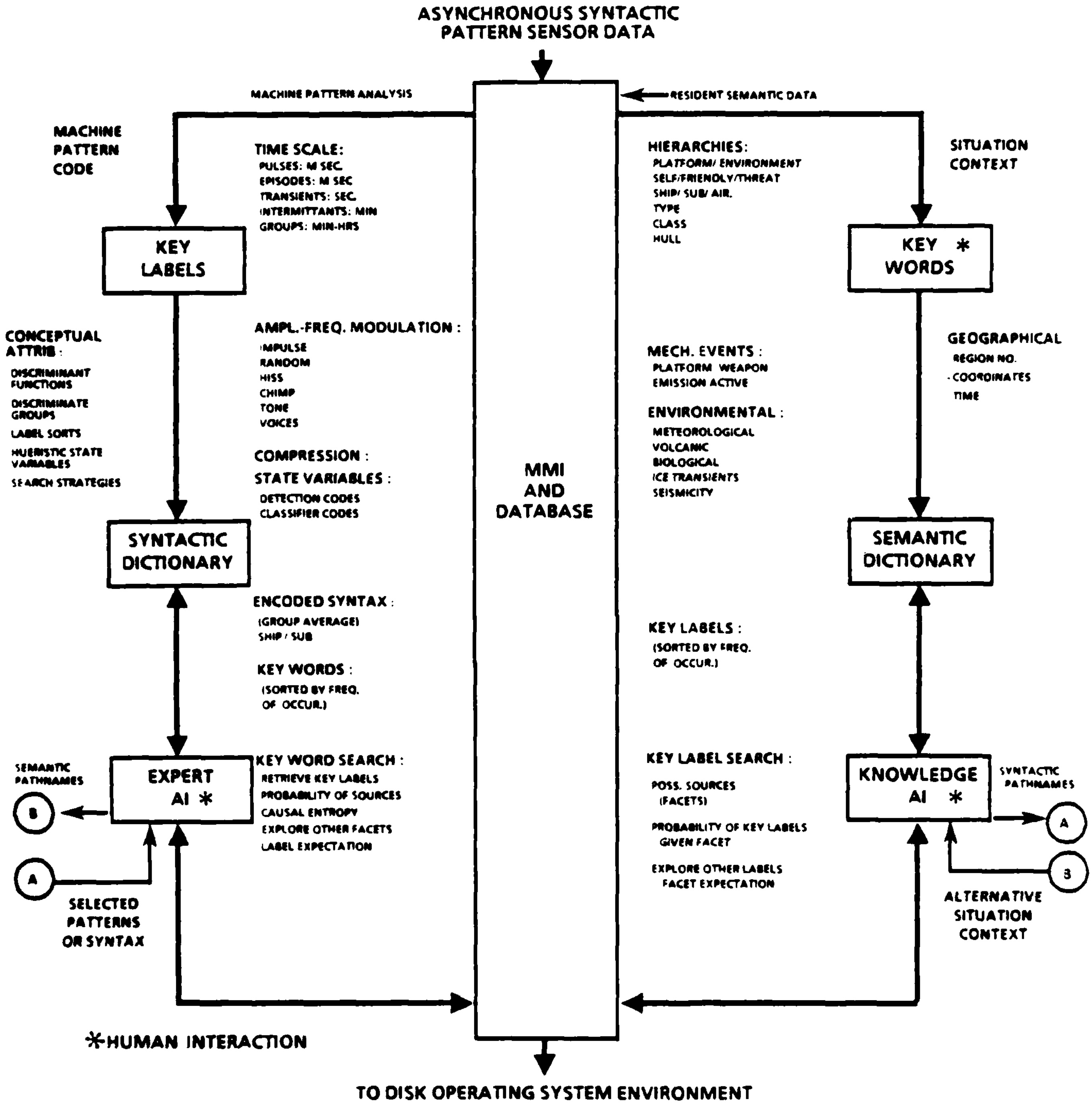

Figure 2-4. Interactive On-line Foreground Process

significant, but which may interfere and degrade classification performance. Excitative classifications are totally under interactive control by the operator. In that case, the function of the automatic background is to generate list-directed pointers to graphical or auditory data files. This is done unobtrusively. A directory is invoked by the operator and scanned for keystroke paths leading to the picture or auditory files required to support an excitative classification decision.

Graphical displays of noise-free representations of possible pattern classifications, under guidance of a classifier mask directory, serve to reinforce operator decisions, i.e., see if the stimulus category was targeted or inhibited; see if stimulus is similar to the "noisy" message to be classified.

In the absence of a perceived required action by the operator, the automatic background processor may invoke an alarm procedure. In that case, the automatic side of the interface prompts the operator for a decision on a stack of transient records it is prepared to display upon the operator's command. For that, the operator could hit a key signifying an authorized presence. After making a classification, the operator optionally could observe a directory list of alternative classifications and generate a report on the classification of any new messages by filtering a pattern catalog to obtain matches. At this level, filtering could optionally involve rearranging columns of attributes by list command, or sorting, scoping, and finding records meeting any prior or newly specified relational requirements. On command, the interactive environment displays a list of filtered features supporting the operator's and other alternative classifications consistent with the current message directory. To the extent that time permits, the final decision is supported not only by feature attributes but by inspecting a hierarchy of classifier masks designed as shortest information paths to targeted sources, and their corresponding pointers to relevant picture or auditory files.

The inhibitive function of classification is important because most transients are irrelevant to operating requirements. They make demands on the attention of an operator, without any value added. These are always present due to abundant own-ship transients, highly structured sources of complex sounds in the local environment, and innumerable random transients indicative of highly complex sources or perturbations of the medium. Suppression of self-noise and other inhibitive signals, which are known to interfere with and degrade the operational response to true excitational stimulus, is performed automatically. The purpose is to suppress these positively identified interfering transient episodes which are known to lengthen reaction times and cause serious classification errors. The operator has a supervisory option of examining the current working directory list of inhibitory messages; displaying the messages with their corresponding mask; in doubtful cases examining picture and auditory files; and if desired, deleting the message from a working directory of the automatic background processor.

2.7 TRANSIENT EVALUATION ENVIRONMENT

Reference to specific operator actions in the above discussion is entirely notional and not indicative of an operable MMI design. Fundamental to the development of both algorithms and MMI is our concept of a transient evaluation environment. The transient evaluation environment is the integration of hardware, software, and actual data into a basic research development and test tool using psychophysical methods and measures of man-machine performance. Formal psychophysical experimentation and analysis provides both the valid measurement of performance and an understanding of underlying human perceptual and cognitive processes relevant to design of classifier systems. Already our classification algorithm research has derived significant benefits from applying human models to automatic processing. Making the machine more man-like can both improve machine performance and provide a common ground to improve operator understanding of background processing capabilities, strengths, and weaknesses.

A parallel, and equally important role for the transient evaluation environment is in the area of transient data analysis and data base development. The identification of invariants in each acoustic transient signal-type across operational parameters such as environment, source constraints, such as limits of operating speed and depth, must be empirically driven as well as based on theoretical grounds. A facility is envisioned; supported by environmental models and data. A functional partition of a transient evaluation environment is illustrated in Figure 2-5. A modular architecture is proposed to facilitate rapid software development and update using "plug in" components. This approach will also translate into tactical software design consistent with rapid tactical updates.

The transient evaluation environment is also capable of supporting transient classifier systems beyond the basic research stage. At this point specific program and system constraints are added and the environment becomes a rapid prototyping facility. Rapid feedback of operator performance is critical in order to cost-effectively determine whether an innovative algorithm or MMI concept helps or hinders typical operator performance. For example, a proposed design concept is tested by operators using known transient signals added to representative

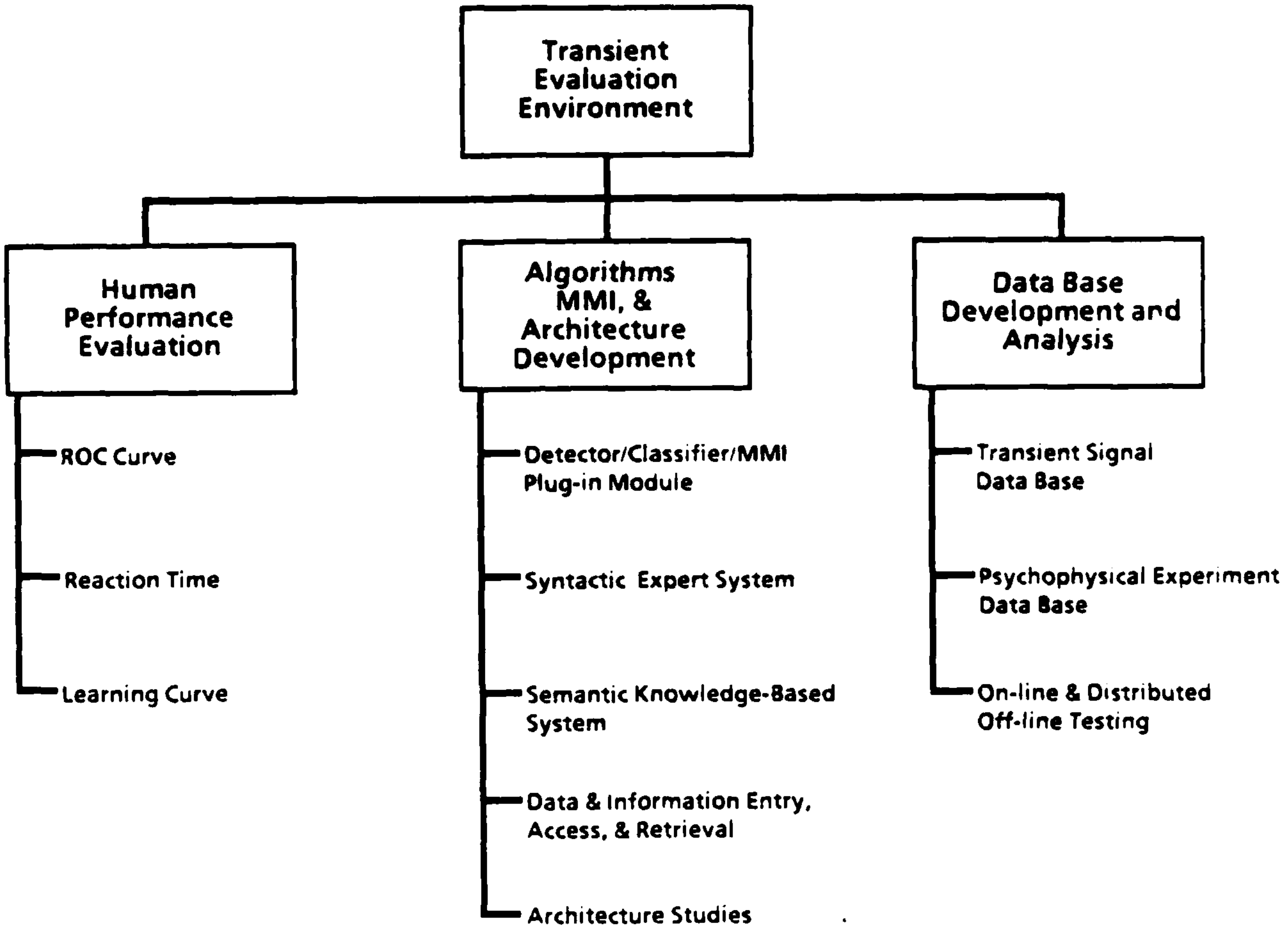

Figure 2-5. Functional Partition of the Transient Evaluation Environment

noise under a range of propagation conditions. The test results are appended to a psychophysical experiment data base. By specifying relational experimental conditions, i.e., propagation range and noise state; relevant receiver operating characteristic (ROC) curves, reaction times, and learning curves can be derived. Test data are selected from a standard pool of typical transient episodes. This includes frequent "noisy" random transients expected in the local environment and structured transients from diverse sources, i.e., biologics, ice, and ownship sources.

To be practical, these benchmarks must be extrapolated from standard tests to other operational situations. This requires validation of predicted performance and variances by psychophysical models. Finally, the transient evaluation environment is critical to life-cycle maintenance, including algorithm/MMI upgrades and data-base update. Psychophysics is needed, not to design experiments to resolve cognitive models, but to perform cognitive interpretation of performance based on the large data base of an ongoing experiment. This is expected to lower the cost and accelerate the rate at which problems are resolved by psychophysics.

3.0 PILOT PSYCHOPHYSICAL EXPERIMENT

This section describes the objectives, procedures, and results of Presearch's pilot psychophysical experiment. The experiment was a joint effort between Catholic University's Human Performance Laboratory (HPL) and Presearch. HPL provided the facilities, including signal processing, displays, experimental control, and data gathering. Experimental design and results analysis were joint undertakings.

The purpose of conducting a psychophysical experiment under our transient classifier systems and MMI research was to establish the feasibility of our proposed transient evaluation environment concept (Section 2.7). The specific objectives of the pilot experiment were threefold: (1) assess the impact of SNR on transient classification, (2) establish performance benchmarks for discrimination against noise (detection), and (3) compare performance between known and novel transient signals. At the beginning of our research, we expected the experiment to raise more questions about the underlying human perceptual and cognitive processes than it would answer. The immediate goal was to direct the research towards areas most relevant to operational situations. The experiment was intentionally structured to promote further inquiry.

3.1 BACKGROUND

The experimental procedure emulated a multisensor-stream scenario typical of a multiple-buoy or multibeam configuration. The scenario assumed the existence of an automatic transient detector ("bell ringer") that monitored all sensor streams, detected possible transients, windowed and processed the raw data, and passed the data to the operator for classification. A monochrome spectrogram or Fastgram (a time verus frequency B-Scan) was selected as the display mode. The operator classified the data in one of three ways: (1) as one of a set of known transients, (2) as a new or unknown transient, or (3) as noise alone (i.e., a false alarm for the "bell ringer"). The operator then proceeded to the next candidate. Although this operating concept is oversimplified, it represents several fundamental operator tasks that are required in an interactive classification system.

The multisensor-stream scenario had reduced semantic or contextual information in that each potential transient snapshot relayed to the operator was independent, i.e., from a different beam or buoy. Thus transient type (target type) and SNR (range) were randomized in successive snapshots (experimental trials). The impact of semantic information from correlated spatial observations, and prior knowledge derived from intelligence and/or other sensors in both the multisensor-stream (search mode) and single-sensor stream (tracking mode), will be a future research effort.

The experiment dealt entirely with actions of the operator related to the transients presented by the assumed "bell ringer." No attempt was made at this stage of the research to integrate a real-time automatic, transient detector into the experimental paradigm. Instead, the transient snapshots were selected beforehand from a digital tape of real data. Gaussian noise was added to the time domain data and each signal was scaled to four different SNRs to emulate propagation loss at various ranges. The use of Navy standard environmental models such as RAYMODE or FACT, and more complex noise models such as Magnum-Moll were deferred to later research. Noise alone cases constitued 25% of the experimental trials, representing a fairly poor "bell ringer." This result is probably not consistent with operational requirements concerning operator workload; however it was required for experimental purposes to collect sufficient data to establish operator false alarm rates.

Experimental design in which transient and procedural parameters are selected and controlled by the researcher represents a necessary non-operational constraint that must be consciously managed to optimize the acquisition and transfer of practical knowledge. Experiments provide variable degrees of freedom and/or direct operational parallels depending on the issues to be addressed. In the design of this experiment, two important departures from psychophysical protocols were made in order to emulate the operational situation. First, noise was added to the time domain data rather than to image space, i.e., directly to the processed display. This step was critical because overlapping Fourier transforms used for Fastgrams would result in noise that was correlated from line to line in the image. Noise added in image space is unrealistic because it is uncorrelated from time to time. To examine transient-classification performance in the presence of noise that is present at the transducer (ambient and self noise), it is necessary to emulate an operational situation and process the noise along with the signal.

The second departure involved scaling the display such that the noise level remained constant regardless of signal SNR, rather than keeping the signal level constant and scaling the noise. The vast majority (if not all) acoustic displays employ the constant noise level approach for sound psychophysical reasons. These reasons include:

(1) maximum use of dynamic range across all noise conditions; (2) consistency in time and across environment; and (3) exploitation of natural biological contour detectors, i.e., neural pathways tuned to spatial and temporal first and second derivatives of energy. Also, operator knowledge of the instantaneous noise condition is secondary to detection/classification of targets themselves. In the current experimental paradigm, scaling the noise instead of the signal would have resulted in a direct cue for target range, i.e., SNR, not available in actual practice. For example, the long-range, low-SNR cases would have generated significantly brighter, average space-luminance on the display if the noise had been scaled up. With the signal scaled to the appropriate SNR, only the signal itself and not the background provided any clues as to target range.

3.2 EXPERIMENT 1

3.2.1 Data Acquisition Preparation

The data consisted of unclassified transient acoustic events stored on three standard magnetic tapes in VAX backup format. The tape files were restored to disk and converted from sequential access to direct access. This resulted in three data files totalling 3516, 4096-point records or over 14 million data samples.

These data samples were compressed by averaging each adjacent three points. This resulted in an effective reduction of the sampling rate from the original 25 kHz rate to an 8.3 kHz rate. Reduction was done to facilitate data handling since the highest transient frequency expected in the data was 4 kHz. (Analyses revealed little information at frequencies even close to this rate.)

3.2.2 Signal Processing

A simple peak detecting algorithm was developed to initially locate candidate transient events in the data. The algorithm was based on a statistical model which was used to predict the value of successive peaks from a moving window of immediately preceding peaks. A peak was defined strictly as the mid-point maximum of three successive points, s(n-1), s(n), and s(n+1) having the relationship (s(n-1) < s(n) and s(n+1) < s(n)) or (s(n-1) > s(n) and s(n+1) > s(n)). First and second order prediction and prediction error statistics were then computed. These were used to predict the intensity of the next peak. A transient event was defined as any peak with an absolute SNR value exceeding the mean of the predictor sample by more than eight standard deviations. Once a transient was located, 8,192 samples (0.98 sec) were extracted for each target.

The peak detector technique identified a "working sample" of approximately 45 of the largest transient events which were then inspected visually using an interactive time-domain editor. A testing set of six transient targets was selected for the experiment trials. A second set of six "null" or background signals was also extracted from the data, one to match each of the six targets. This was accomplished by sampling from records which were temporally contiguous to the target records. Hence, background noise plus steady-state signatures were comparable across the target and null sets.

An 8,192-point FFT was performed on each of the target samples. Inspection of these data revealed harmonically-related spectral bands as a distinguishing feature of these transient events.

A spectrogram was constructed for each of the target samples by computing 256, 256-point FFTs on adjacent samples (approximately 31 ms) of the data, advancing successive FFTs by 31 samples (approximately 3.7 ms). The log of the spectral magnitudes from this analysis was used to construct 256 x 256 pixel images which depicted the time-varying frequency composition of each signal. Visual inspection of these data revealed clear harmonic patterns, frequency glides, and broadband characteristics for each of the transient events.

The actual test imagery was constructed by adding Gaussian noise with zero mean and unit standard deviation to the signals in the time domain before carrying out the spectrographic analysis. Signal-to-noise ratio was varied by scaling the signals to yield ratios of 20, 14, 8, 2 and -4 dB between the peak of the signal and the Gaussian noise. The 20 dB case was used in the preview segments of the experiment and the remaining four SNR cases were used in the test trials. The images were all scaled to have approximately equal space-average luminance on a monochrome video monitor.

Image preparation, control of the experimental events, and data analyses were carried out on a general-purpose laboratory computer (Digital Equipment Corporation VAX 11/750). The computer served as the controlling host for a Gould Imaging and Graphics IP8400 image processing system which was used for on-line image processing, storage, and presentation. Participants were seated in a soundproof testing room, with low-level ambient light, imagery was viewed on a high-resolution, 14-in. (30.5-cm) diagonal, monochrome monitor (Ikegami Model PM14-3H). Standard raster frequencies and an interlaced 30 Hz frame rate were used with a display resolution of 512 by 512 8-bit pixels. Participants sat at a viewing distance of 122 cm and entered responses on a computer terminal keypad.

Sixteen paid undergraduate volunteers served as the observers in each of two experiments. The participants were told that the $10.00 flat fee could be augmented by a potential $4.00 bonus for good performance. All participants received the maximum $14.00 for participating in the experiment regardless of performance.

3.2.3 Procedure

During a preview stage, the participants were shown three signals. Below each signal a letter was displayed. The letters A, B, and C were used to designate the three signals the observers were shown. The observers were instructed to study and remember each signal and associate the signal with the letter that appeared beneath it. Following the signals, three noise fields were displayed for the observers to familiarize themselves with nonsignal trials. This process was then repeated a second time. The preview session also served to familiarize the students with the actual response procedures used during the test blocks. The instructions for the proper keypad responses were presented on a video monitor which was located to the left of the observers.

The experiment consisted of six blocks of 96 self-paced trials, administered in two sessions of three blocks each. Each session occurred on a different day. Before each block of trials for each test session, the preview stage was repeated. In each block, six signals, three that were shown in the preview, and three novel signals, were shown. Each signal was presented three times in each of the four signal-to-noise ratios. There were 24 nonsignal trials in each block. Signal type, SNR, and nonsignal trials were presented in random order for each block.

During each trial the observers' task was to classify the spectrogram as either noise alone, as a specific "known" signal (A, B, or C) or as a new or "unknown" signal. This first phase of responses was to classify between noise alone and any signal condition. Their response choices were "1" for definitely no signal present, "2" for probably no signal present, "3" for probably a signal present, and "4" for definitely a signal present. If the observers chose response "3" or "4," they were then asked to identify the signal by pressing one of four contiguous keys: "A" for signal A, "B" for signal B, "C" for signal C, or "O" ("other") if there was a signal present but it was not one of the three signals shown in the preview. After making a response, feedback appeared on the display. If, in truth, the trial consisted of a known target signal A, B, or C; then the appropriate letter (A, B, or C) was displayed on the monitor. If, in truth, the trial consisted of a novel target signal or non-signal (no target present) then the character "?" appeared on the monitor. When ready to go on to the next trial the participants pressed the key labelled "continue." Upon completing the sixth block of trials, observers were asked to complete a short questionnaire regarding the experiment. The experimental briefing and questionnaire given to each student is given in Attachment A (Section 3.5).

The sixteen participants were broken into four groups of four based on which three transients were in the "known" group (i.e., those which are presented during the preview sessions and have explicit feedback during testing). The grouping was selected in order to separate transients 1, 2, 3, and 5 that are dominated by harmonic components from transients 4 and 6 which are not. The grouping was also used to test interaction between two very similar transient events (1 and 2) both of which consisted of three distinct episodes and were positionally located at the bottom of the spectogram display. The resulting groupings were:

Group	Transients in Preview Feedback Set
1 :	1, 2, 6
2 :	3, 4, 5
3 :	1, 4, 6
4 :	2, 3, 5

The transients in the "preview/feedback set" will be referred to as the "known" transients for each subject in the remainder of the report. The novel transients will be referred to as "unknown." The preview set grouping ensured that each transient type was used in the same number of known and unknown trials combined across subjects.

3.2.4 Results and Discussion

3.2.4.1 Detection Results

The four-point confidence scale used by the participants to discriminate the presence of a transient against the noise alone, was used to derive the Receiver Operator Characteristic (ROC) curve for each subject and collapsed across subjects for each SNR. The area under this curve was then calculated using a trapezoidal algorithm. This performance measure was chosen to avoid an unnecessary Gaussian assumption. The results by block are illustrated in Figure 3-1. The ROC area indicated that the performance on the detection task quickly reached asymptote and that the impact of SNR was substantial. Figure 3-2 illustrates that performance for the unknown transient group is only slightly

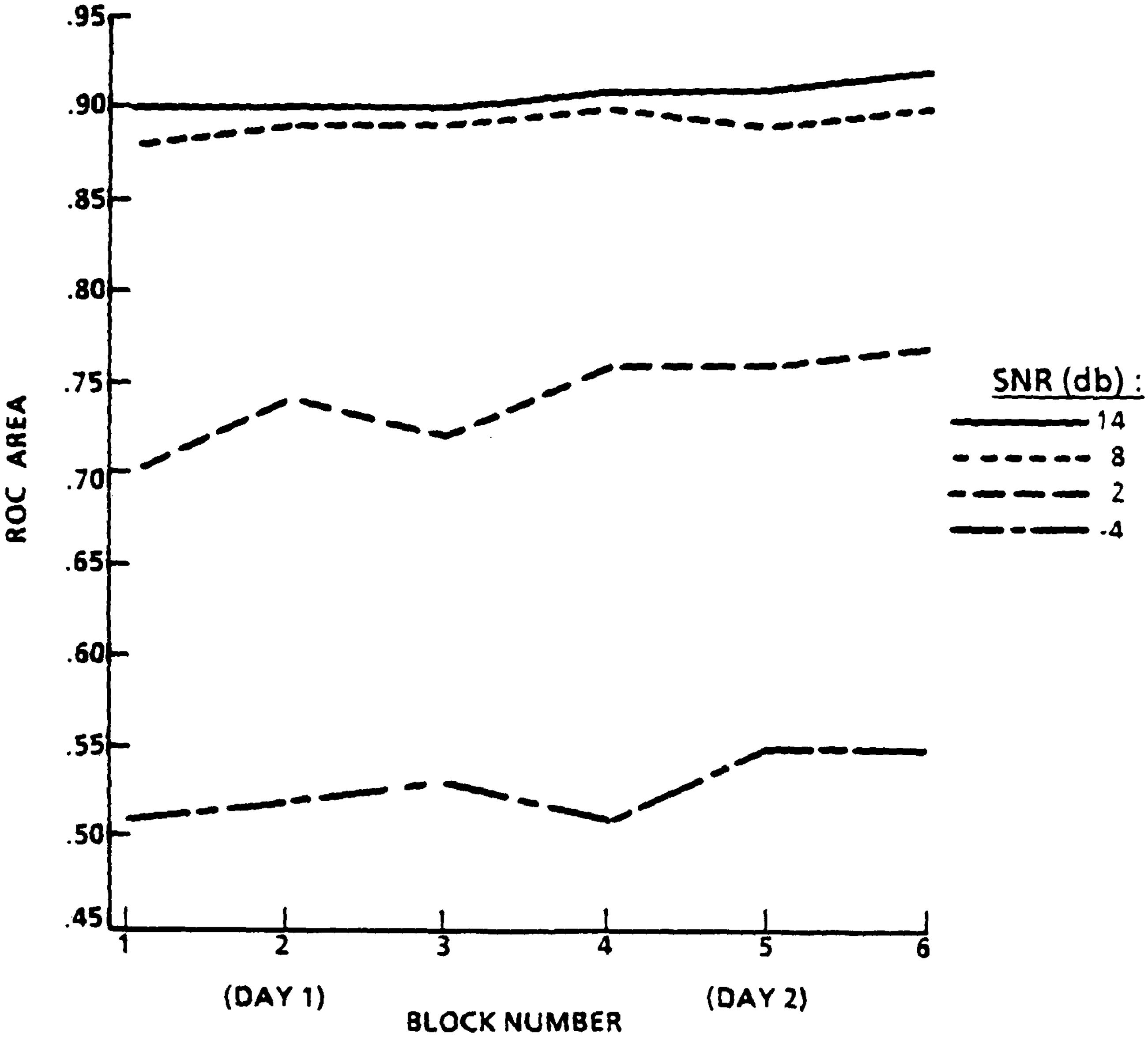

Figure 3-1. Detection Performance Learning

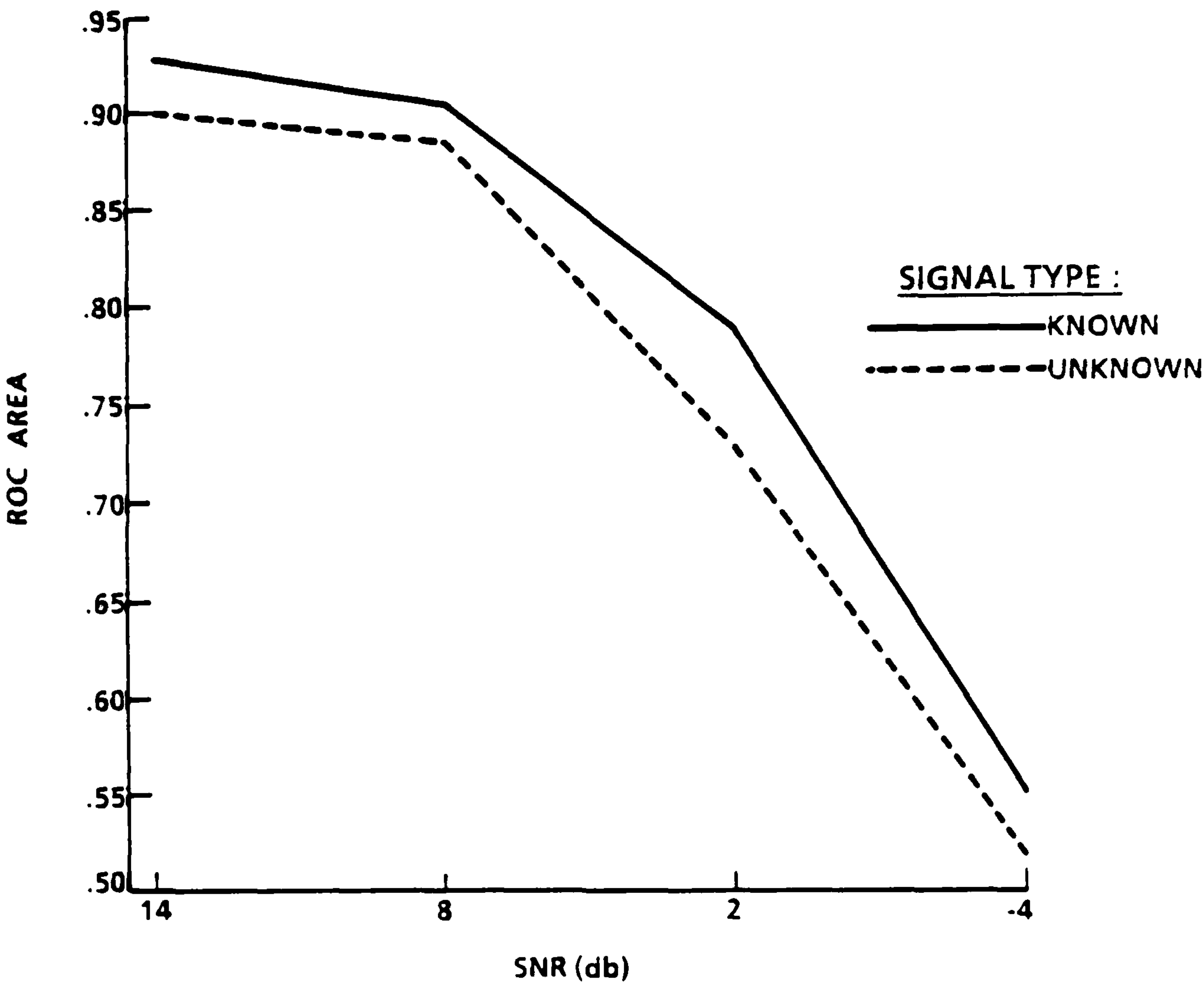

Figure 3-2. Impact of SNR on Detection Performance

worse than for the known transient group. A mixed design analysis of variance substantiated the significance of SNR ($\underline{F}$ (3,45) = 57.53, $\underline{p} \leq .01$) and the known vs. unknown group difference ($\underline{F}$ (1,15) = 6.92, $\underline{p} \leq .05$) with no interaction ($\underline{F}$ (3,45) $\leq$ 1.0).

The performance difference between the known and unknown signals is shown by block in Figure 3-3. The percentage of subject responses to either response key 3 (probably signal present) or 4 (definitely signal present) is used as a performance measure to illustrate that the learning exhibited at the two high SNRs for the unknown group is twofold: increased number of hits, and fewer false alarms. Performance at the two high SNR cases over the later blocks indicate that subjects did indeed recognize the unknown transients as valid target signals. It is most likely that the lack of feedback, particularly at the difficult lower SNR cases, was the reason for the reduced performance compared to the known transients. This is supported by the large difference between performance on known vs. unknown for the two low SNR cases.

At the lowest SNR the significance of ROC area over chance performance can be obtained by determining the variance of the chance ROC curve. For equally likely responses across the four point scale, each of the responses is marginally distributed as binomial with p = .25 from a multinomial distribution. The number of subject trials at a given SNR level for a single block by group (known or unknown) is 144, resulting in a ROC area requirement of .5402 for significance at the .05 level (using the normal approximation). For the SNR = -4 dB case, detection performance for known transients was significantly above chance for blocks 2, 3, 5, and 6 (recall that block 4 was the beginning of the second day). For unknown transients detection performance was significantly above chance only for block 6. The

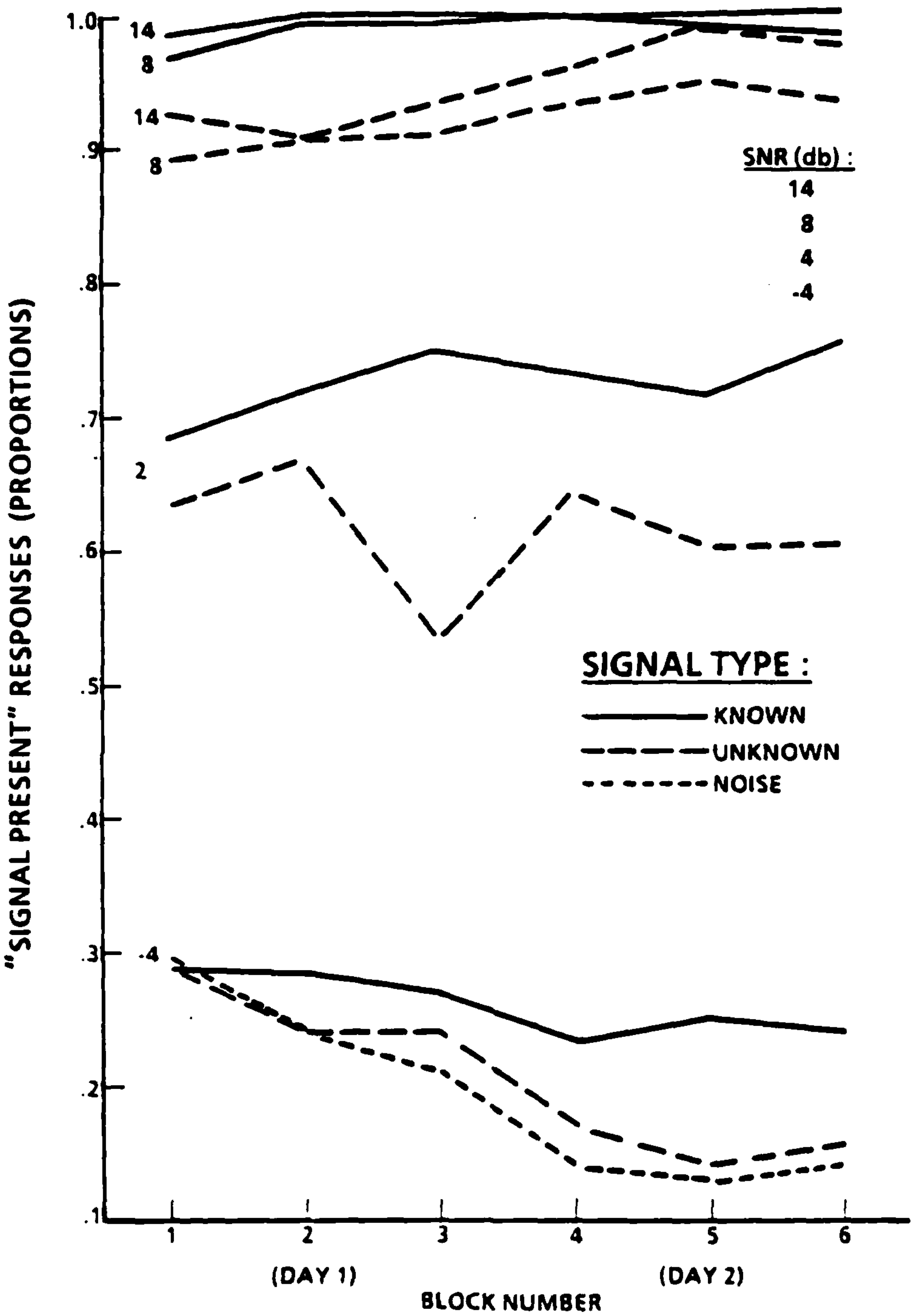

Figure 3-3. Proportion of "Signal Present" Responses

implication is that the feedback condition provided transient specific low SNR training, possibly resulting in unique low SNR strategies. Some transfer to the unknown transients is evident by the above chance performance at +2 dB SNR and by the slight learning trend at -4 dB SNR. It is unlikely that the preview experience was a critical differential factor because the high SNR trials for the unknowns served a familiarization (observation) function similar to the preview trials for the knowns.

Transient specific composition (syntax) is shown to be a significant factor in the disparity between detection performance on known and unknown transients by the nonparametric SIGN test broken out by preview set in Table 3-1. Although the significance level for the hypothesis that performance is better on known transients for all trials is .0143, it is readily apparent that strong differences in the previous sets exist. Only two of the four preview sets were significant, although a third demonstrated a similar trend (preview set 1, 2, 6 ; p = .1938). Transients 3 and 5 were common known signals for the two preview sets that did show significant performance enhancement for the known condition, and were common unknown signals in the two remaining preview sets. Transients 1 and 6 were common in the opposite fashion. The subjects in preview set 3 (known transients = 1, 4, 6) performed significantly better on <u>unknown</u> transients (p = .9979 that known performance is greater than unknown performance, translates into p = .0021 that unknown performance is greater than known since there were no ties). All three of the unknown transients had strong harmonic components in only this preview set. Sufficient data is not available to perform meaningful statistics on each individual transient type by SNR and by known/unknown grouping. At this time it is impossible to draw any stronger conclusion than that the preview/

feedback condition appears to improve detection performance, particularly at low SNR, but that transient specific syntax is an even more powerful indicator of performance.

Table 3-1. Comparison of Detection Performance on Knowns vs. Unknowns

Preview Set	N	X	P
1,2,6	12	8	.1938
3,4,5	16	15	.0003
1,4,6	16	2	.9979
2,3,5	16	14	.0021
Total	60	39	.0143

N = number of subject/SNR sets

X = number of cases with area under ROC curve greater for "Knowns"

P = significance level for x (sign test table for N 40, normal approximation for N 40)

3.2.4.2 Detection Performance Benchmark

The "null" or "background only" data samples associated with each transient were used to determine the SNR between the background alone and the Gaussian noise added in each of the four specific transient peak-to-noise SNR cases examined. This information was used to determine the performance required by the best current broadband sensor to match the experimentally derived transient detection performance. The results of the transient experiment were translated into a false alarm probability per watch equivalent to current broadband sensors, and used a probability of detection of .5 to ensure accurate comparison. The transient "bell ringer" assumed in the experiment procedure was taken to "autodetect" one possible transient event for operator confirmation/denial every 670 seconds when trained on noise alone (i.e., it was a bell ringer resulting in over 250 operator decisions per hour for full azimuthal coverage).

The detection performance realized in block 6 of the experiment for known transients and collapsed over subjects was 1 dB worse than the theoretical best performance for current broadband sensors. This result is promising considering the untrained and unscreened subject pool and the nonoptimized man-machine interface. Two experienced sonar operators were tested on a single block of trials and demonstrated performance that was 12 dB better than the subject pool. These results are not entirely unexpected, given the combination of signal characteristics and display type used. It remains to be seen how the more complicated transmission loss and ambient noise conditions in the actual acoustic environment will effect this preliminary result. The precise performance characteristics of the bell ringer (or no bell ringer at all) and additional operator workload under considerations of concurrent and/or multiplexed tasking will also be critical factors determining operational performance.

3.2.4.3 Classification Results

Figure 3-4 illustrates the conditional probability of correct classification by group (known vs. unknown) given detection. A Spearman statistic test for trend showed that learning was significant at the .05 level for both knowns and unknowns at SNR 14, 8, and 2 dB; but not at SNR -4 dB. The most striking learning was for the unknown group at high SNR as expected from the detection results. It is interesting that classification performance at an SNR of 2 dB is grouped with the higher SNRs for the known transients yet for the unknown transients it is

KNOWN SIGNALS

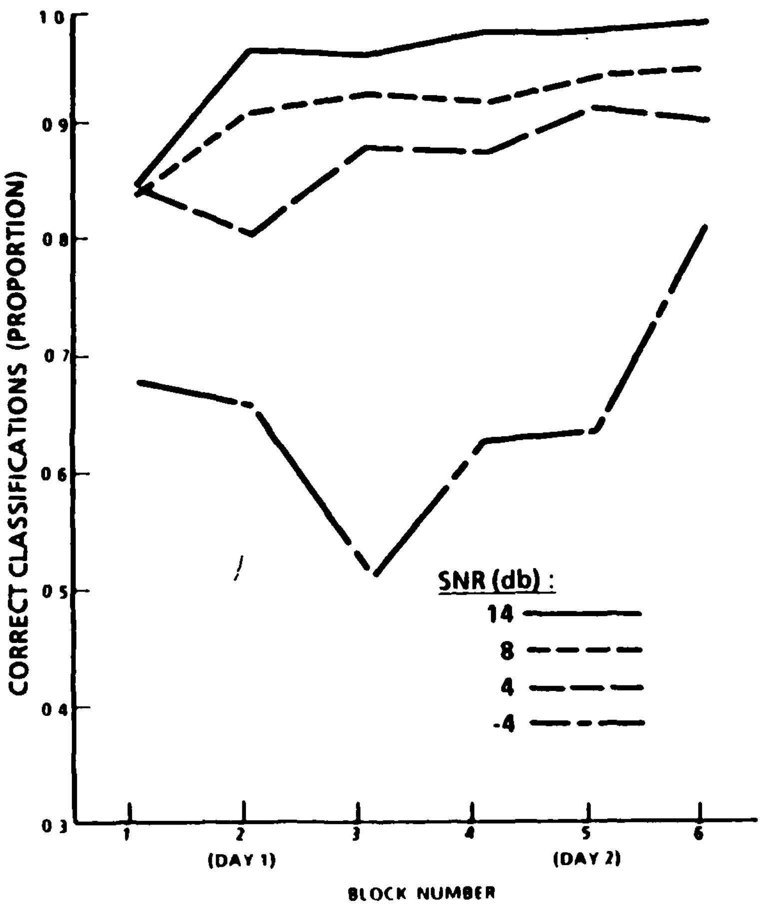

Figure 3-4a

UNKNOWN SIGNALS

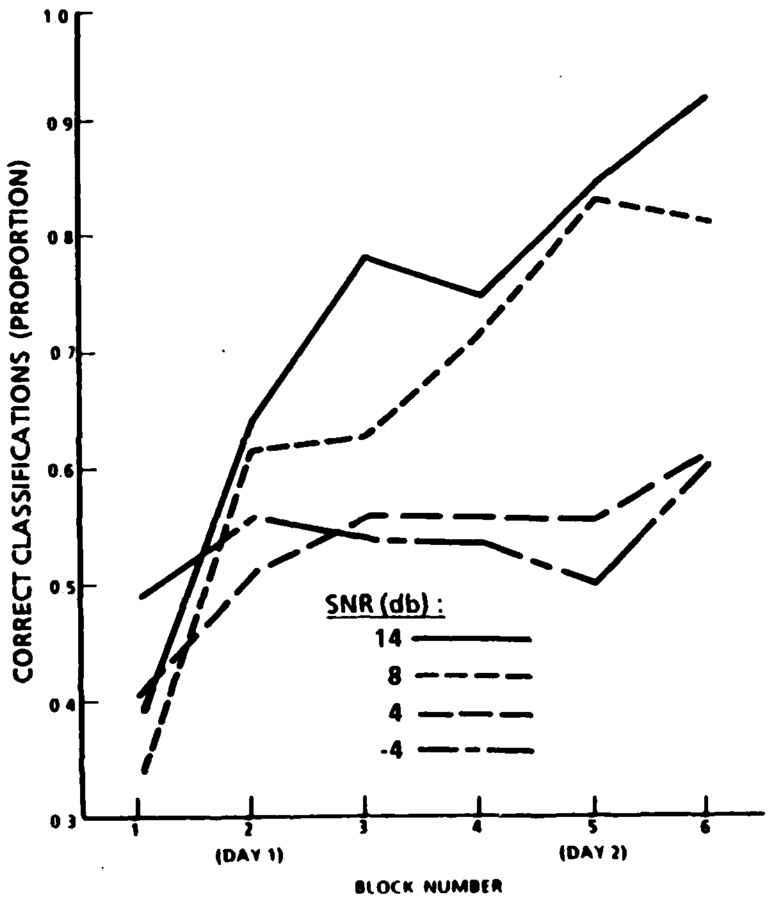

Figure 3-4b

Figure 3-4. Classification Performance

grouped with the lowest SNR case. As in the detection analysis, the feedback condition has shifted the performance curve. The result in classification is, however, more surprising because given detection, it is reasonable to predict that feedback that "crystallizes" the perception of all known signals would complementarily enhance rejection of all other signals.

Note that chance responses to the four choices will yield a probability of correct classification by group of .75 for the knowns and .25 for the unknowns. Note also the responses based on presentation ratio (perceived by subjects as the a priori probability) would result in a probability of correct classification by group of .50 for both groups. Classification performance of the -4 dB SNR unknowns and noise cases suggest that classification responses were influenced by the presentation ratio rather than being pure chance. Noise alone cases that were false alarms were classified equally into the two groups (probability of classification of unknown given detection of noise was .486). Recall also that detection performance for unknowns was not significantly above chance at -4 dB SNR. An alternative explanation is that responses were chance but based upon an internally developed known/unknown dicotomy. This can be tested with another experiment where the presentation ratio between known and unknown is other than 1:1. The classification performance of knowns at -4 dB SNR falls below chance response, also supporting the argument that classification responses were not purely chance key presses. Classification performance for the knowns at -4 dB was better than presentation ratio based responses supporting the detection performance results that showed detection performance significantly above chance.

Figure 3-5 shows the probability of correct classification by signal type (i.e., A for A, B for B, C for C) for the known cases. Chance response is .25 for this measure of classification performance, while the presentation ratio based response is .167. The relationship of classification performance across SNR remains the same for performance measured by type or by group; however, it is clear that classification performance by signal type for knowns at -4 dB SNR is better than responses based upon chance and/or presentation ratio alone. Classification performance is also greater than chance responses between only the known alternatives given classification within the known group (.22, .22, .17, .20, .21, .27, respectively for each block). The most consistent feature used to classify as indicated by the subjects in the questionnaire was the transient position on the time axis. Fourteen of the sixteen subjects used positional clues in their descriptions of the signals. This clue is consistent with the assumption of a bell ringer automatically isolating and windowing the data, although the consistency of the window will in fact be sensitive to SNR. Experiment 2 examines the impact of removing this clue by altering the position in time of each transient from trial to trial.

The impact of SNR on classification performance given detection is summarized in Figure 3-6. The drop-off in classification performance illustrates sensitivity to SNR. It also indicates that detection does not guarantee correct classification. This result is consistent with one group of common psychophysical models of classification as the joint combination of several independent discrimination judgments. In the current experiment, the independent discrimination judgments would be differentially sensitive to SNR resulting in classification that demonstrated associated performance variation with SNR. Each transient type exhibits its own unique relationships between

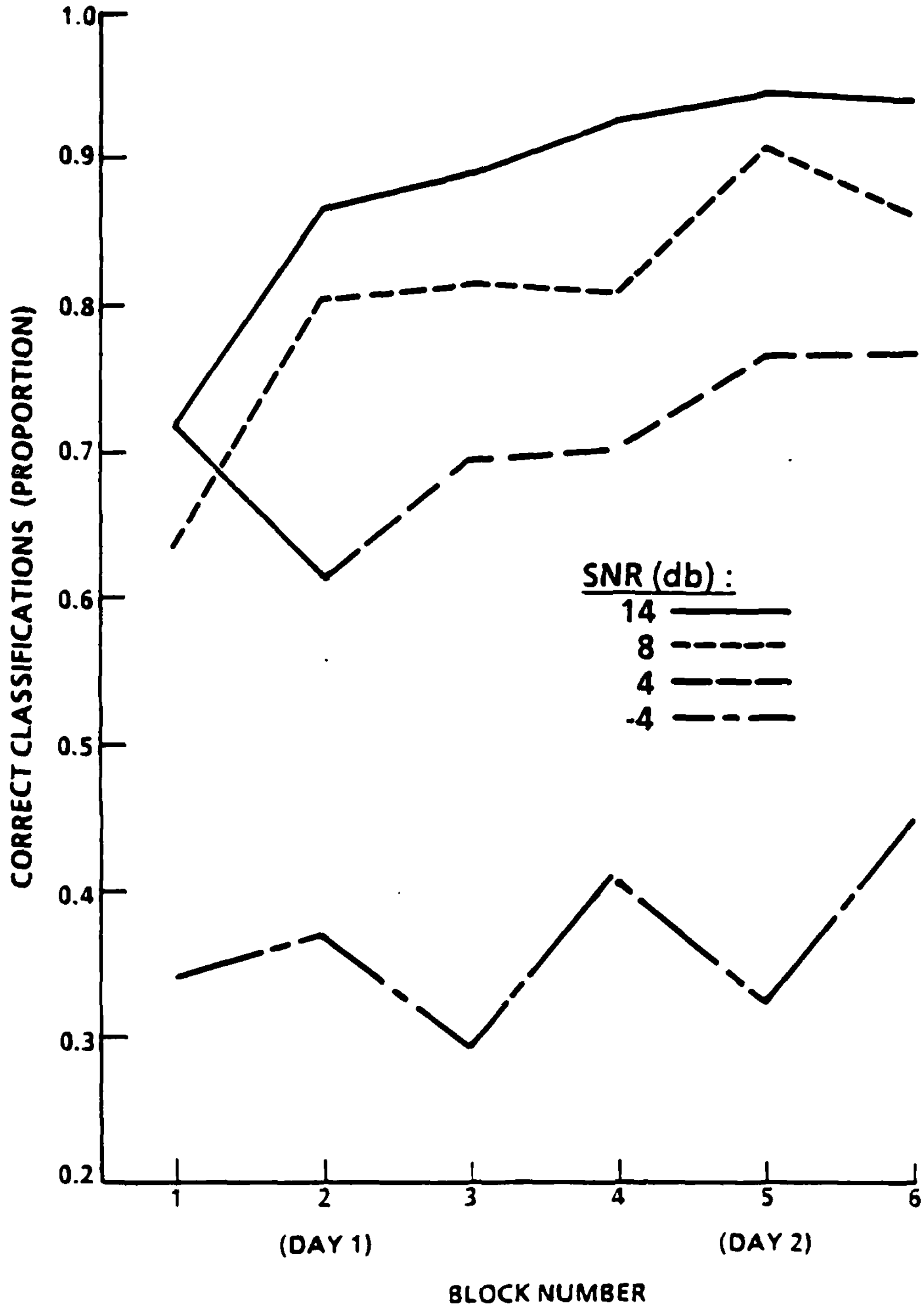

Figure 3-5. Impact of SNR on Correct Classification of Known Transients

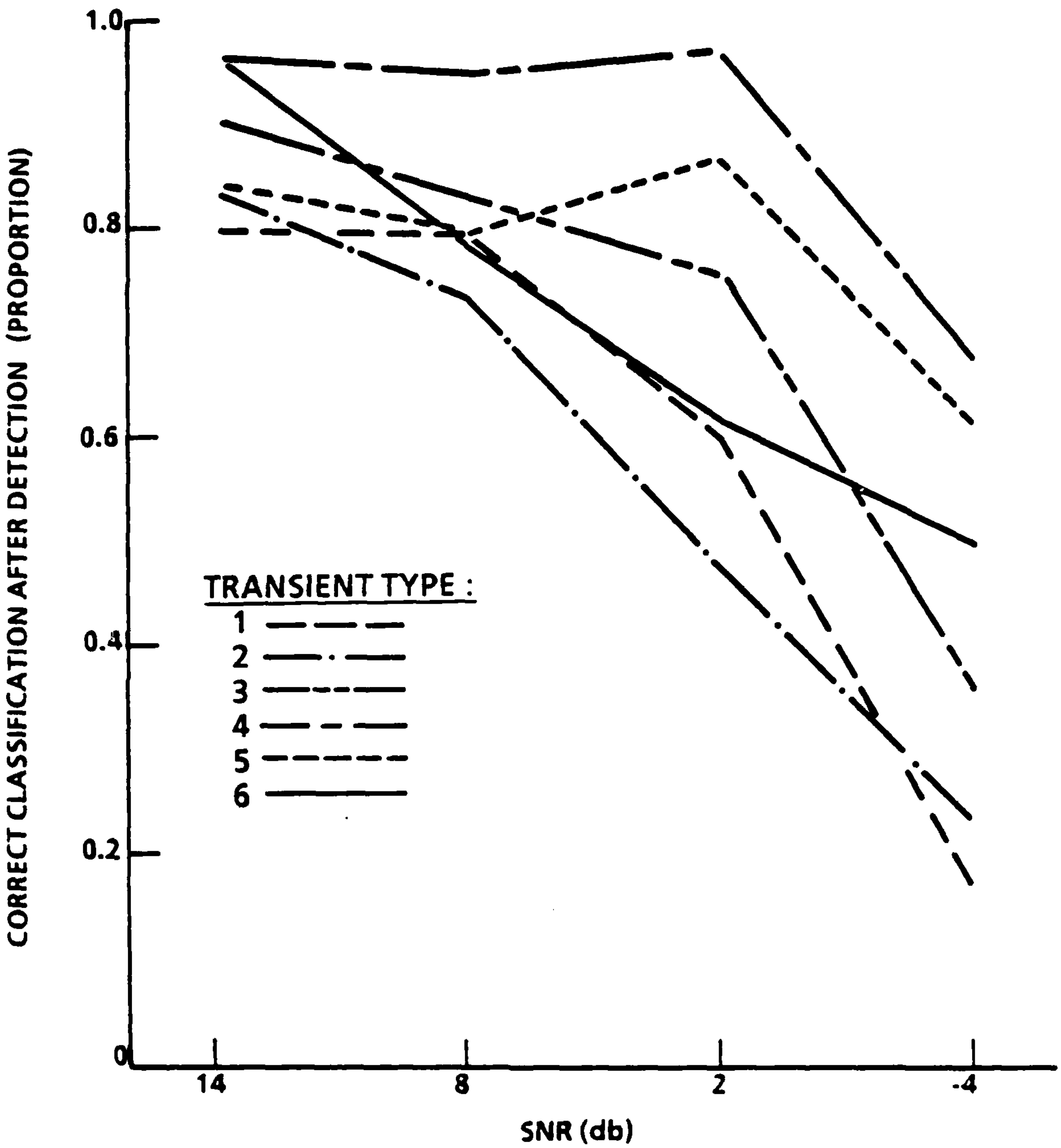

Figure 3-6. Classification Performance of Known Transients

discrimination parameters and SNR as evidenced by the different shapes of the classification performance curve. Other approaches to explaining the relationship between detection and classification have not beeen addressed in this study. An intriguing, but at this time inconclusive observation is that classification is more difficult than detection at high SNR, but relatively easier than detection (compared to chance) at low SNR.

3.2.4.4 Response Latency Analysis

Figure 3-7 shows the mean latency for correct detection responses (i.e., probably or definitely signal present) and correct noise responses (i.e., probably or definitely no signal present) collapsed across subjects. Analysis of variance was performed by filling the few holes in the individual subject data (for example no detections at -4 dB SNR in block 2 for subject 12) with the average latency for that condition across subjects. Results indicated that SNR was significant at the .01 level ($\underline{F}$ (3, 45) = 30.86). The responses cluster into two groups by SNR, suggesting the possibility of two different perceptual/cognitive detection processes; one at high SNR and another at low SNR. Subjects supported this hypothesis by describing detection responses at high SNR as "almost automatic or reflexive" followed by a classification judgment and the classification response. On the other hand, at low SNR, the detection decision appeared to the subjects as intimately linked to the ability to correlate the perceived pattern with one of the remembered target signal patterns (including any unknowns already identified by their repetitive presentation at high SNR). This hypothesis predicts that the classification latency associated with the low SNR cases will be relatively shorter than for the high SNR cases because the classification decision has already been reached.

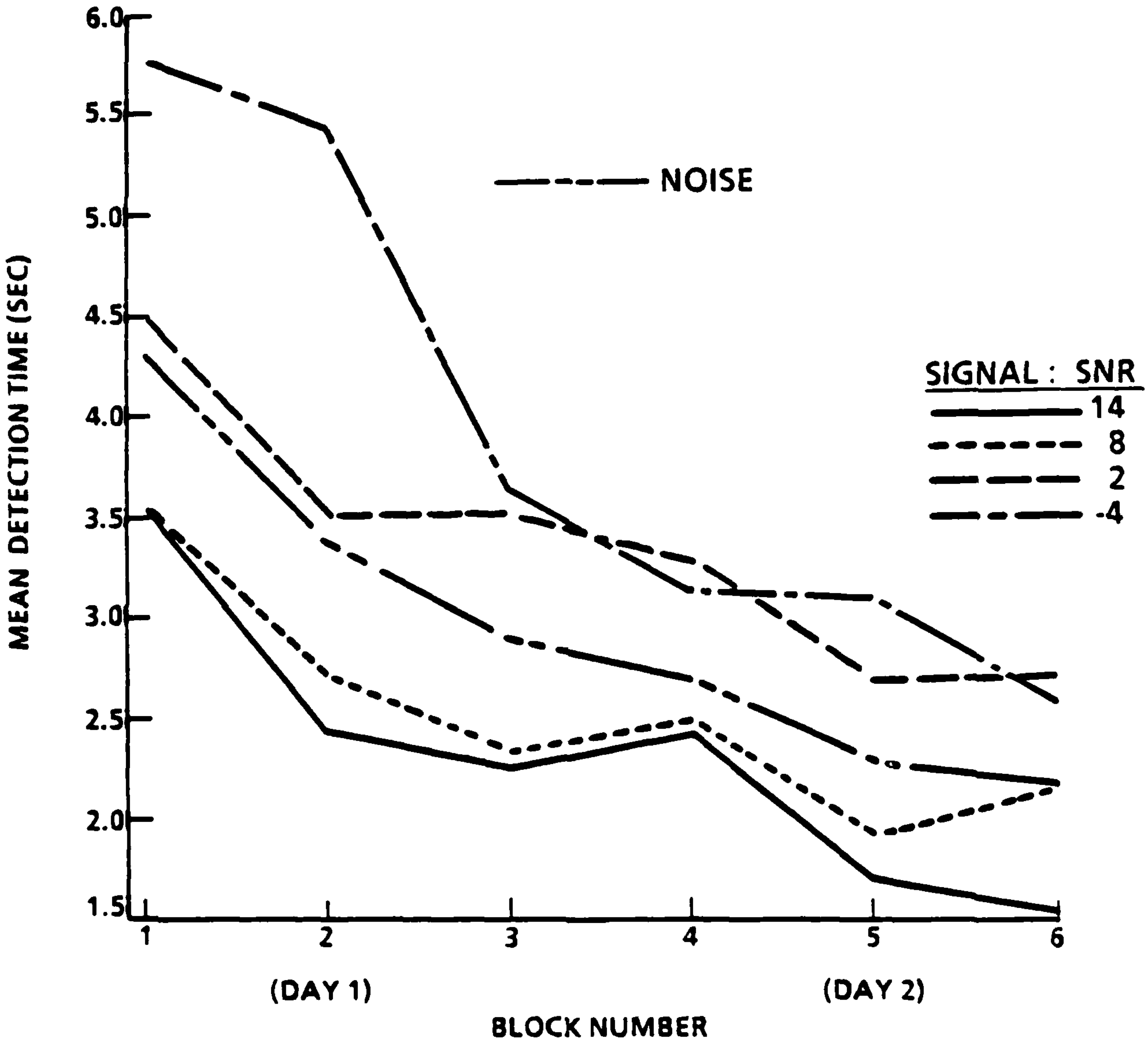

Figure 3-7. Impact of SNR on Detection Latency

To check this prediction, classification latency was examined as a function of SNR. The mean latency between the detection response and the classification response is shown collapsed over subjects in Figure 3-8. Interpretation of the classification latency results is difficult because on any given trial a subject need not make the physical detection response prior to making a classification decision (i.e., he could make the detection decision and the classification decision internally prior to making any physical response). The classification latency in these cases is primarily represented by the time needed to find the appropriate key corresponding to the desired classification label. (It is assumed the operators would not arbitrarily adopt a strategy to minimize the classification latency by first locating the appropriate detection and classification keys and then preparing to hit them rapidly in sequence.) Note that this type of response is exactly what was expected for the low SNR cases if hypothesis of mutual detection and classification decision-making at low SNR is valid.

Figure 3-8 demonstrates an increasing trend in classification latency as SNR drops from 14 dB to 2 dB with a reversal at the lowest SNR case. The difference in latency with SNR was significant ($\underline{F}$ (3, 4763) = 5.18, $\underline{p} < .005$) based on an analysis of variance. An additional pairwise comparison of the means (using the normal approximation due to the large number of samples) indicates three possible groupings of latency shown in Table 3-2. An optimal grouping analysis (including the best number of groups) is not practical for the current experimental paradigm. It is however significant to note that the reversed trend is significant (the -4 dB SNR classification latency is significantly lower than the 2 dB SNR case) which lends support to the hypothesis of combined detection and classification decision-making at the lowest SNR. Classification latency for

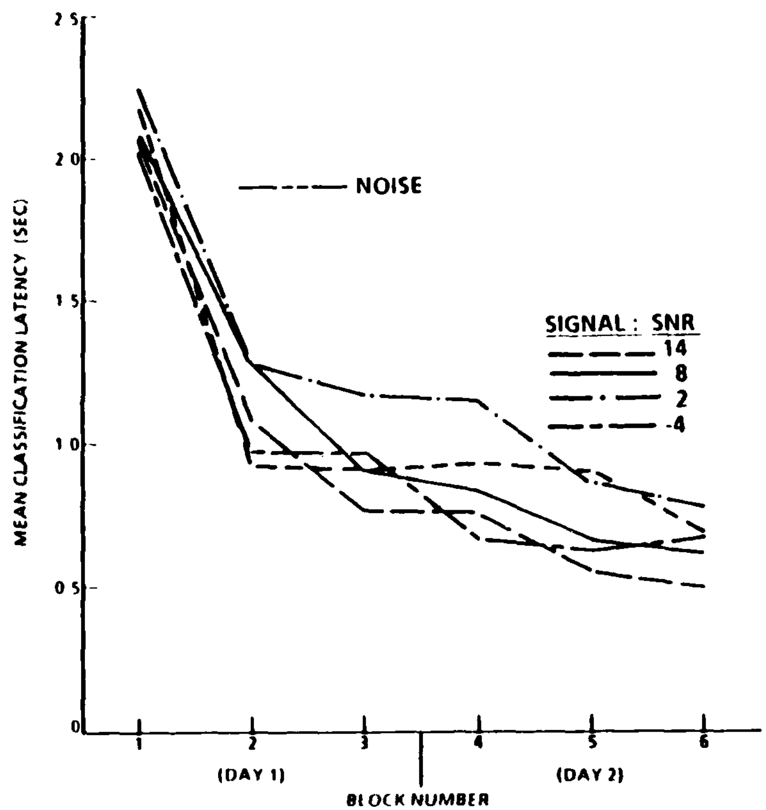

Figure 3-8a

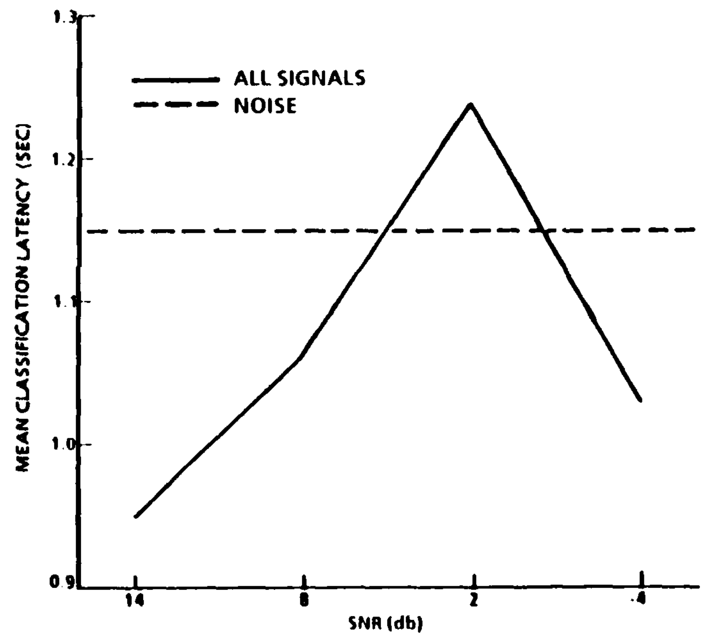

Figure 3-8b

Figure 3-8. Classification Latency

the noise trials was not significantly different than the -4 dB SNR trials, which also supports this hypothesis. Additional parameters in the hypothesis are required to explain why the 2 dB SNR case is the only case demonstrating significantly different response latency than the -4 dB case. No speculation is made of what those parameters might be at this time.

Table 3-2. Significant Grouping of Classification Latency

STIMULUS CONDITION (ORDERED IN ASCENDING CLASSIFICATION LATENCY)				
14 db	-4 db	8 db	NOISE	2 db
GROUPS NOT SIGNIFICANTLY DIFFERENT				

The classification latency results also indicate that classification response latency nearly reached asymtote by block 2 and the maximum absolute difference between SNR cases is less than 0.5 seconds. These differences in classification times are not great enough to alter the monotonically increasing latency of detection with decreasing SNR, i.e., the total time to detect and classify remains monotonically increasing with decreasing SNR.

Figure 3-9 reveals additional clues toward understanding the decision-making process used by the subjects by examing both hits and misses for signal and noise stimuli. A pairwise comparison of the means resulted in significant differences (at the .05 level) between the groups indicated in the figure. At the two high SNRs, correct and incorrect responses had identical latency and this latency was significantly faster than any responses to the noise trials. This result when combined with the high ROC area found in section 3.2.4.1 suggests that misses at high SNR may have often been incorrect physical key strokes rather than incorrect detection decisions. In other words, a very short response latency is an indication of the presence of a signal regardless of the response (signal or noise) actually entered. This has potentially direct application to MMI design, by suggesting that an automatic check of response latency could be used to direct the operator to doublecheck rapid signal absent responses for keystroke error.

Examination of the detection latency for noise and -4 dB SNR stimuli indicates a significant response biased latency. For these trials, it is only the response, and not the stimulus, that is correlated to latency. Responses indicating a signal was present (signal hits and false alarms) took longer than responses that a signal was absent (signal misses and noise hits). The low SNR stimulus case can be treated the same as a noise trial for this analysis because of the low detection performance for this case (ROC area = .529). This simplifies the question: Why should a false alarm take longer than a correct noise determination when the stimulus is the same. Two possible explanations are postulated: (1) additional mental processing pertaining to classification is done after the detection decision and before the detection response, and/or (2) One or more consistent perceptual features occurred in the noise trials that

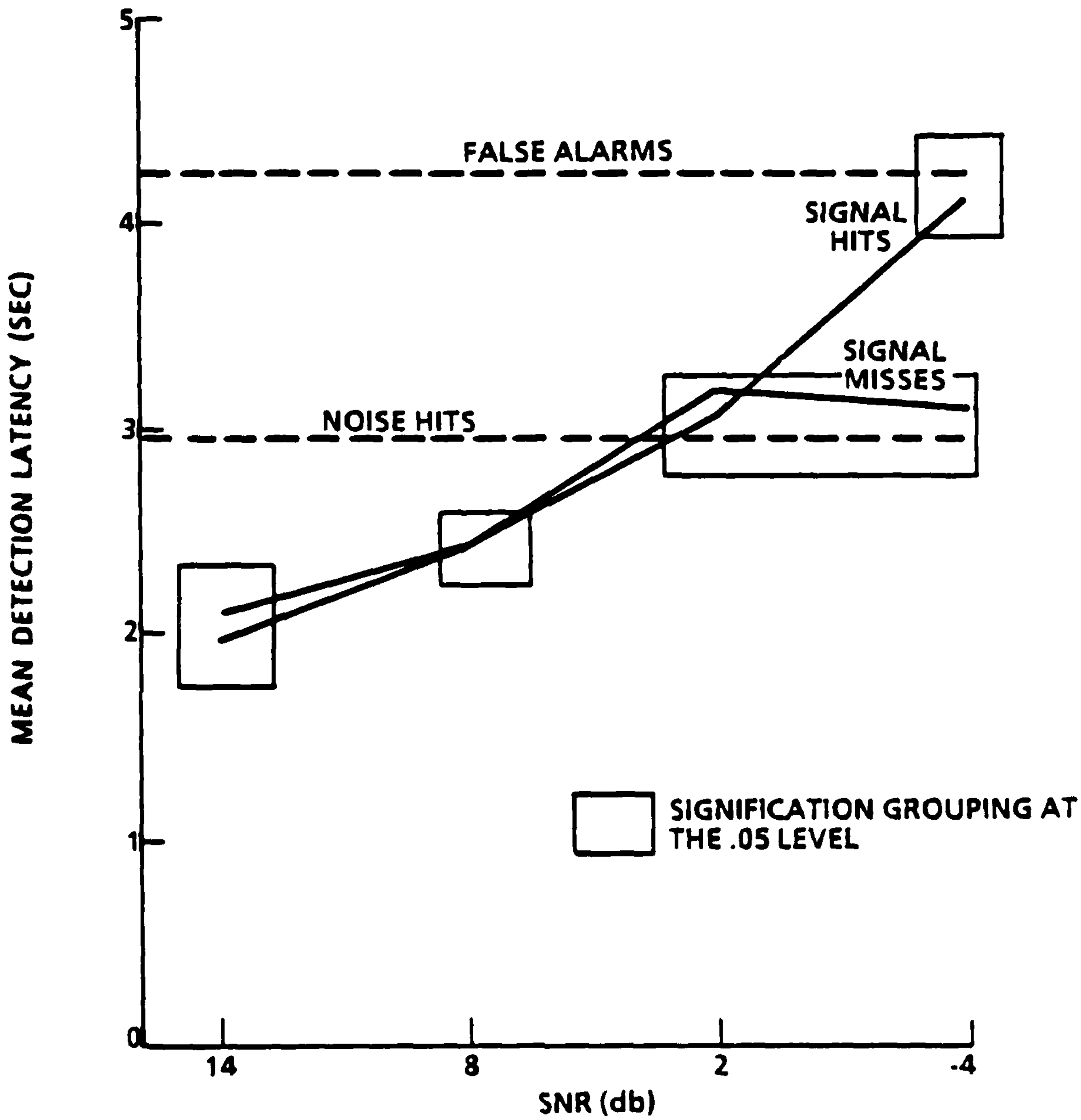

Figure 3-9. Comparison of Latency Between Signal and Noise Responses

were called as false alarms and these features did not occur in the noise trials correctly identified (i.e., the stimuli as perceived by the subject were not the same). An analysis across blocks illustrated in Figure 3-10 indicates that the response based latency phenomenon only occurs during the learning phase.

The effect of the known and unknown group on detection latency is illustrated in Figure 3-11. An mixed design of variance indicated some significance between knowns and unknowns (F (1, 15) = 3.21, 05 < P < .10) and no interaction with SNR (F (3, 45) = 1.0). The difference between the known and unknown group was predominantly at low SNR. Classification latency between groups was nearly identical. A possible explanation for the crossover observed in Figure 3-11 is that once sufficient learning takes place, the subjects developed a heirarchical classification structure using a known vs. unknown decision preceding the classification by type required for the known signals. The grouping of all unknowns into a common response set then eliminates the time spent remembering additional, finer level classification rules required for the known group.

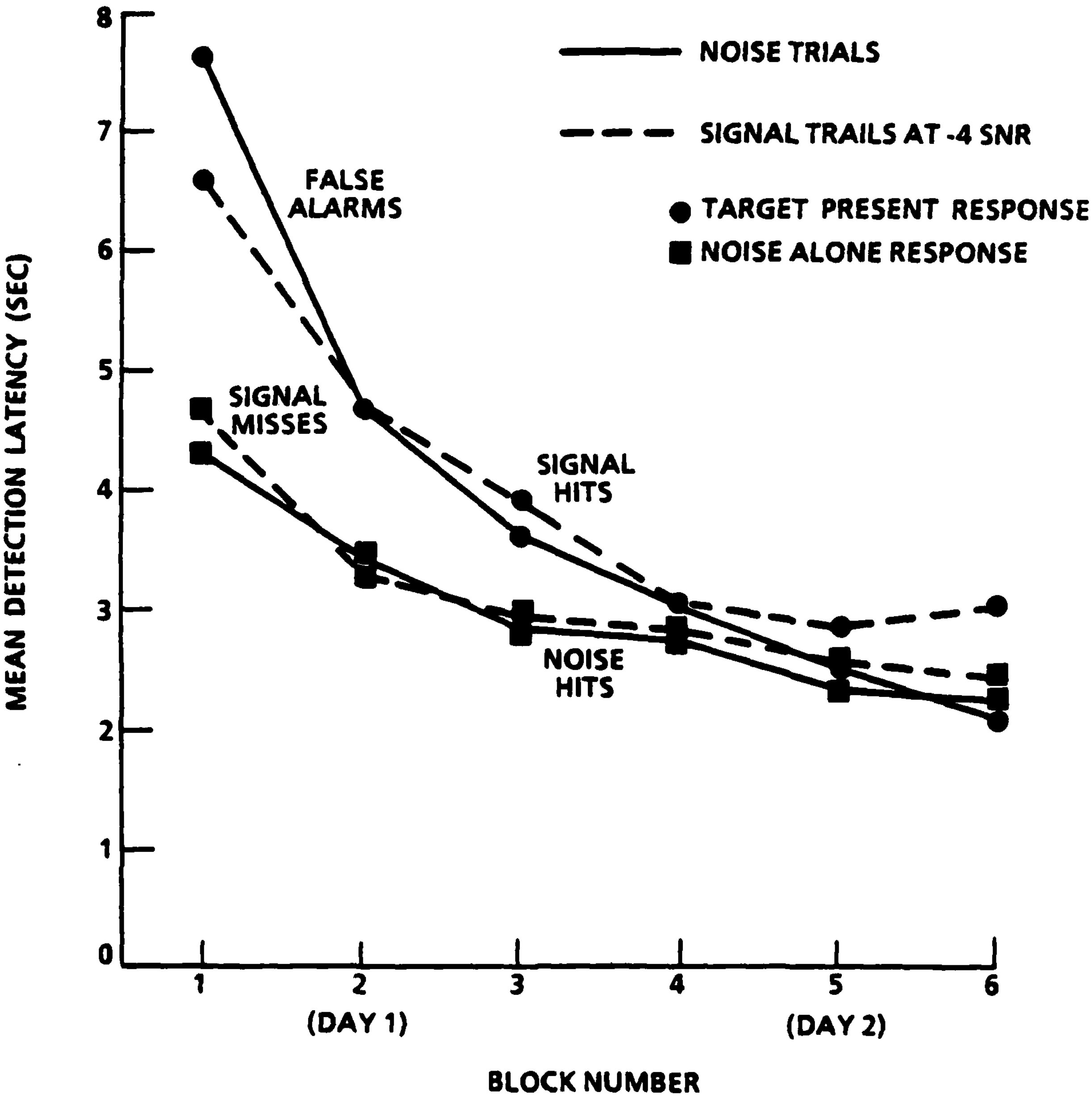

Figure 3-10. Detection of Noise and Signals at -4 SNR (Experiment 1)

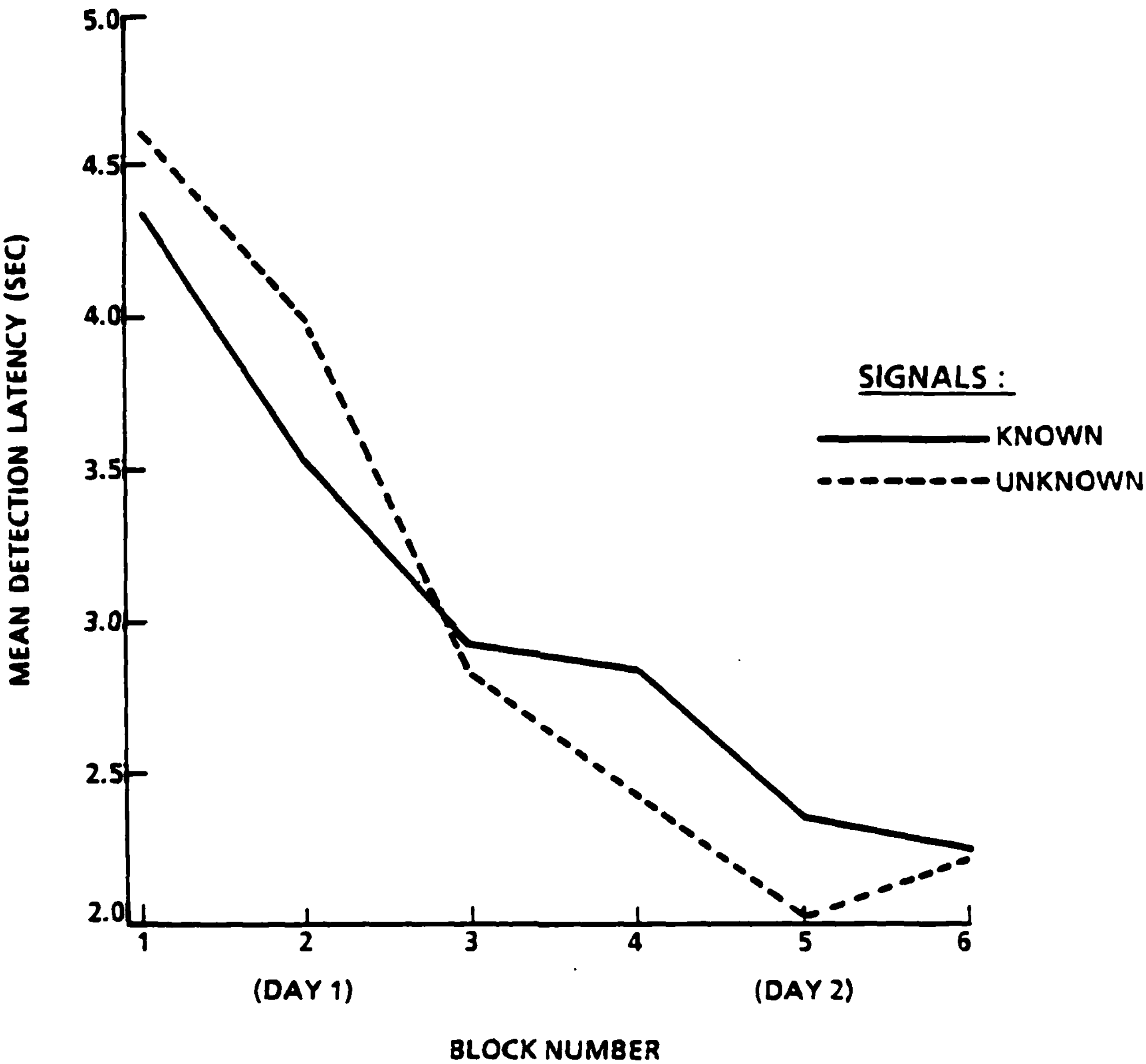

Figure 3-11. Comparison of Detection Latency for Known and Unknown Signals (Learning Curve) (Experiment 1)

3.3 EXPERIMENT 2

3.3.1 Overview

Experiment 2 was conducted to test the performance of the participants for transients having no position clues on the vertical axis. The variable positioning of transient signals along the vertically oriented time line was devised so as not to allow the participants to make position related detection and classification decisions. Below is a comparative study between the results of Experiment 2 and those already mentioned of Experiment 1. Conclusions concerning Experiment 1 which are not further discussed in this section should be assumed to be consistent with Experiment 2.

3.3.2 Results and Discussion

3.3.2.1 Detection Results

Detection performance in Experiment 2 was nearly identical to Experiment 1, with Experiment 2 having a slight reduction in detection performance overall (Figure 3-12). ROC areas did not increase with each successive block for all SNRs; in fact, only -4 dB signals show conclusive learning. In contrast, the high SNRs have decreased ROC areas over successive blocks during each day. This phenomenon is not completely understood; however, there are two ways an ROC area can decrease:

(1) False Alarms. An increase in false alarms is expected with an increasingly aggressive strategy to correctly detect signals.

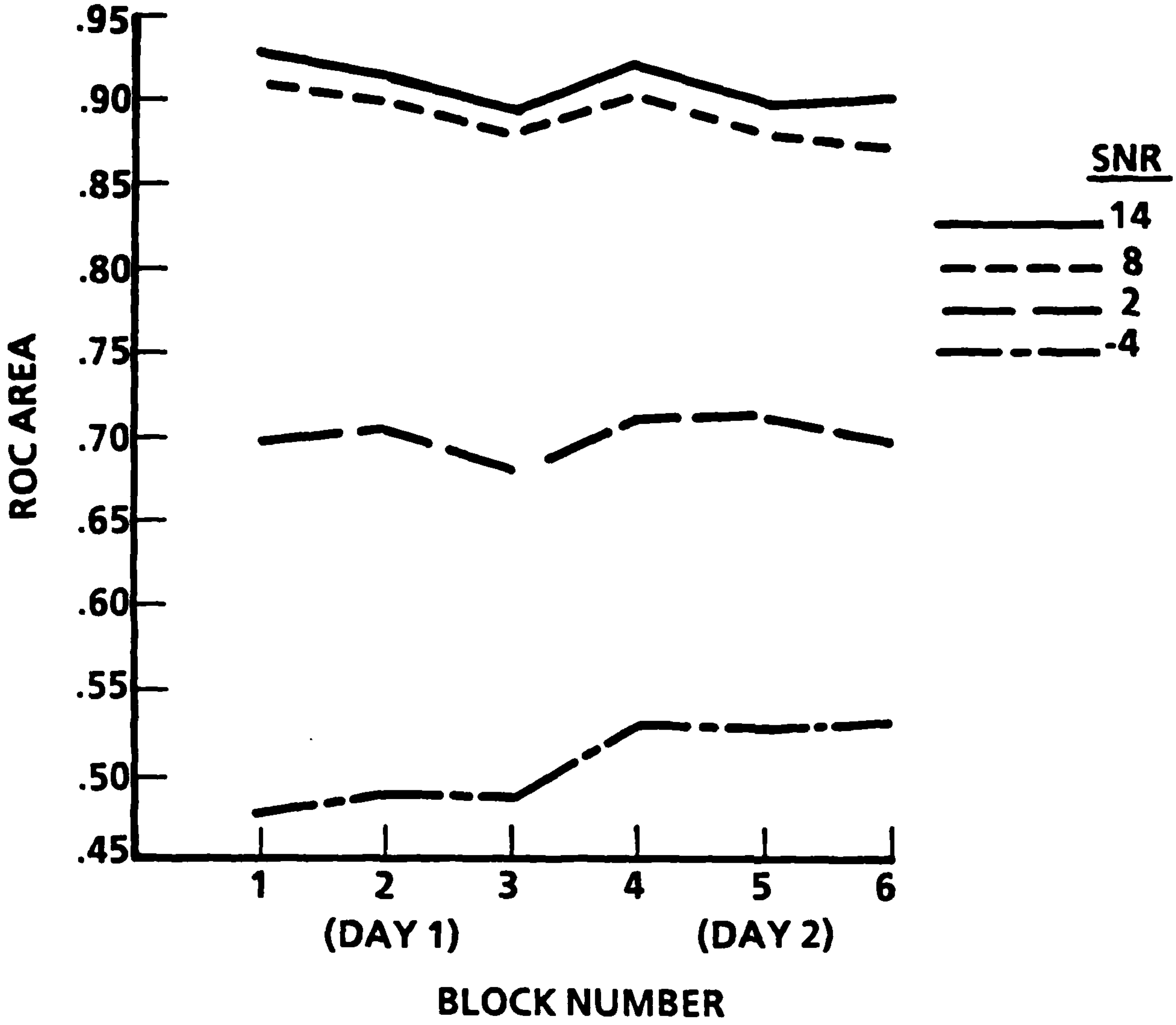

Figure 3-12. Detection Performance (Learning Curve) (Experiment 2)

(2) Signal Misses. The increase of signal misses for high SNRs is a difficult concept to explain. For low SNRs, this increase can be attributed to an increasingly conservative strategy. However, for high SNRs, signals are difficult to miss, unless, because of the length of the experiment, the participant has become increasingly distracted and has consequently lost concentration.

Unfortunately, it is difficult to conclude whether one or both are occurring. Also, -4 db signals have ROC areas which fall below the random threshold of 0.50. ROC areas calculated for known and unknown signals (Figure 3-13) are nearly identical to those of Experiment 1, known signals having consistently greater ROC areas.

The percentage of detection for signal present responses for known and unknown signals (Figure 3-14) was also nearly identical to data collected from Experiment 1. A few exceptions existed: for unknown signals at -4 dB analyzed over blocks, the percentage of signal present responses was at times lower than that of noise. This indicates that statistically speaking, the participant was unable to differentiate between the two. Also, the percent of signal present responses for noise is consistent throughout all blocks, whereas in Experiment 1, the percent decreases over successive blocks. The implications are that participants in Experiment 2 did not learn from their previous mistakes (false alarms). In fact, during both Experiment 1 and Experiment 2 there is no feedback to the participant indicating false alarms; therefore, results in Experiment 1 which show a decrease of false alarms over successive blocks (learning) was unanticipated.

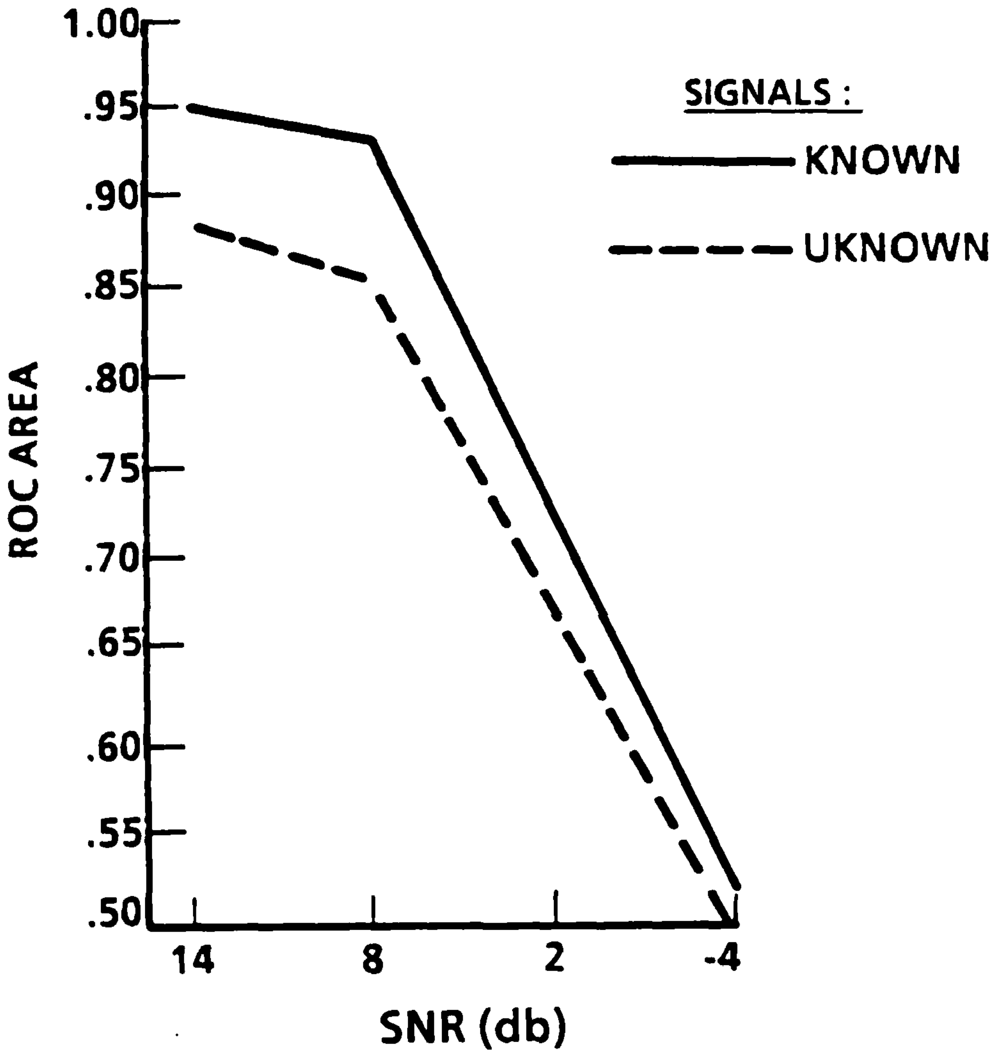

Figure 3-13. Comparison of Detection Performance for Known and Unknown Signals (Experiment 2)

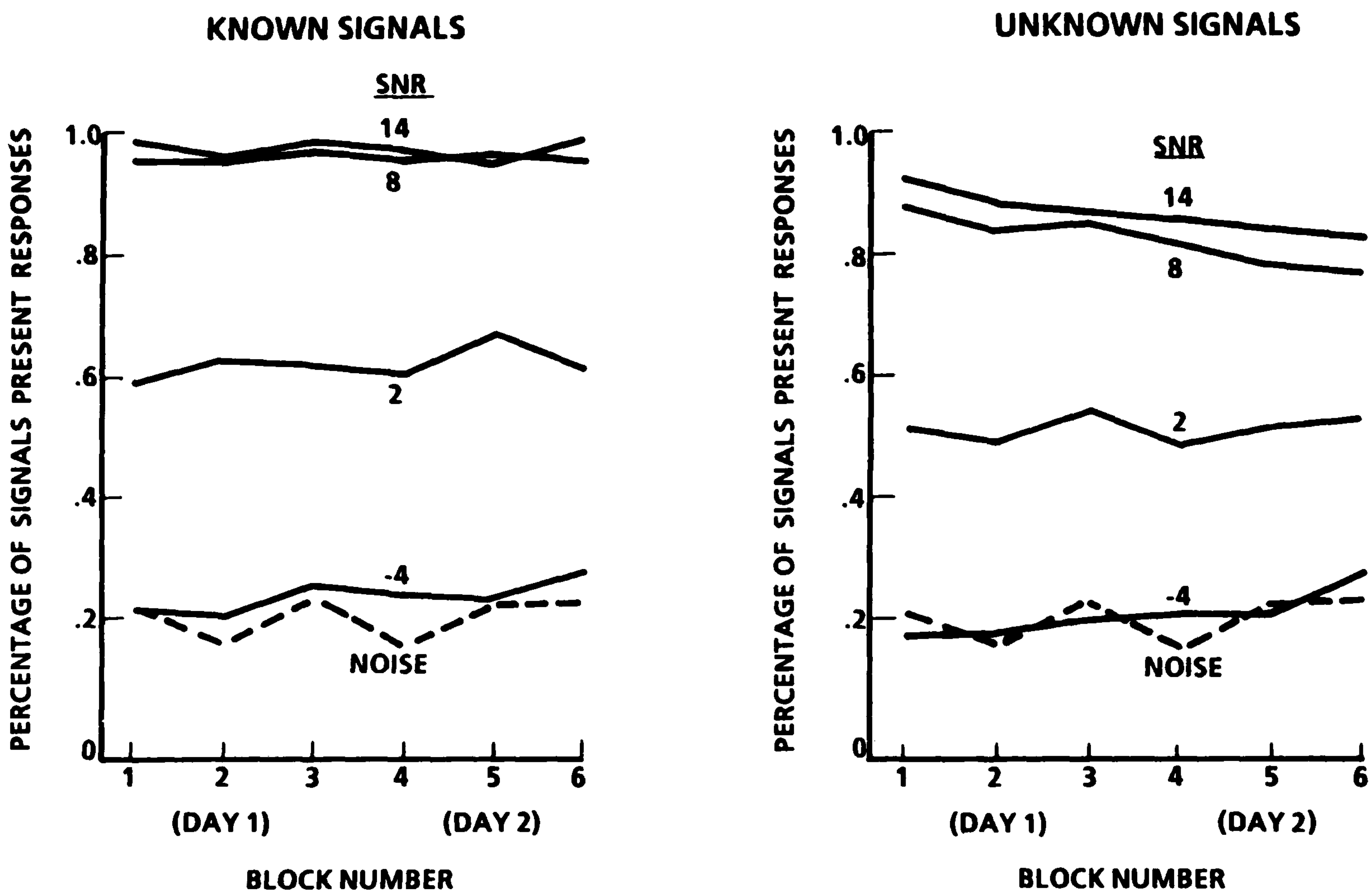

Figure 3-14. Percentage Indicating Signal Present Responses (Experiment 2)

3.3.2.2. Classification Results

Classification performance was slightly different in comparison to Experiment 1. The percentage of correct classification for known signals by group analyzed over blocks showed that the 2 dB signals were grouped with the -4 db signals, as opposed to being grouped with the high SNRs in Experiment 1 (Figure 3-15). This indicates that for Experiment 2, the unfixed position of the transients caused the classification performance threshold to increase, making signals of lower SNR levels increasingly difficult to classify. Table 3-3 graphically shows the detection threshold in relation to specific classification clues (discriminants) for a green SNR. Types of clues would include different light patterns and their associated positions.

Table 3-3. Classification Performance Threshold

Experiment 1	Experiment 2
Clue 1	Clue 1
← Threshold For -4 db Signals	← Threshold For -4db Signals
Clue 2	
← Threshold For 2 db Signals	← Threshold For 2 db Signals
Clue 3	Clue 3
Clue 4	Clue 4
← Threshold For 14 db Signals	← Threshold for 14 db Signals
Clue 5	Clue 5

All clues above each of the thresholds represent clues that have a greater than 50% chance of being observed, while those below the thresholds have a less than 50% chance. Clue 2 might represent the position-related discriminants. Also, as anticipated, for increasing SNR, more clues are observable.

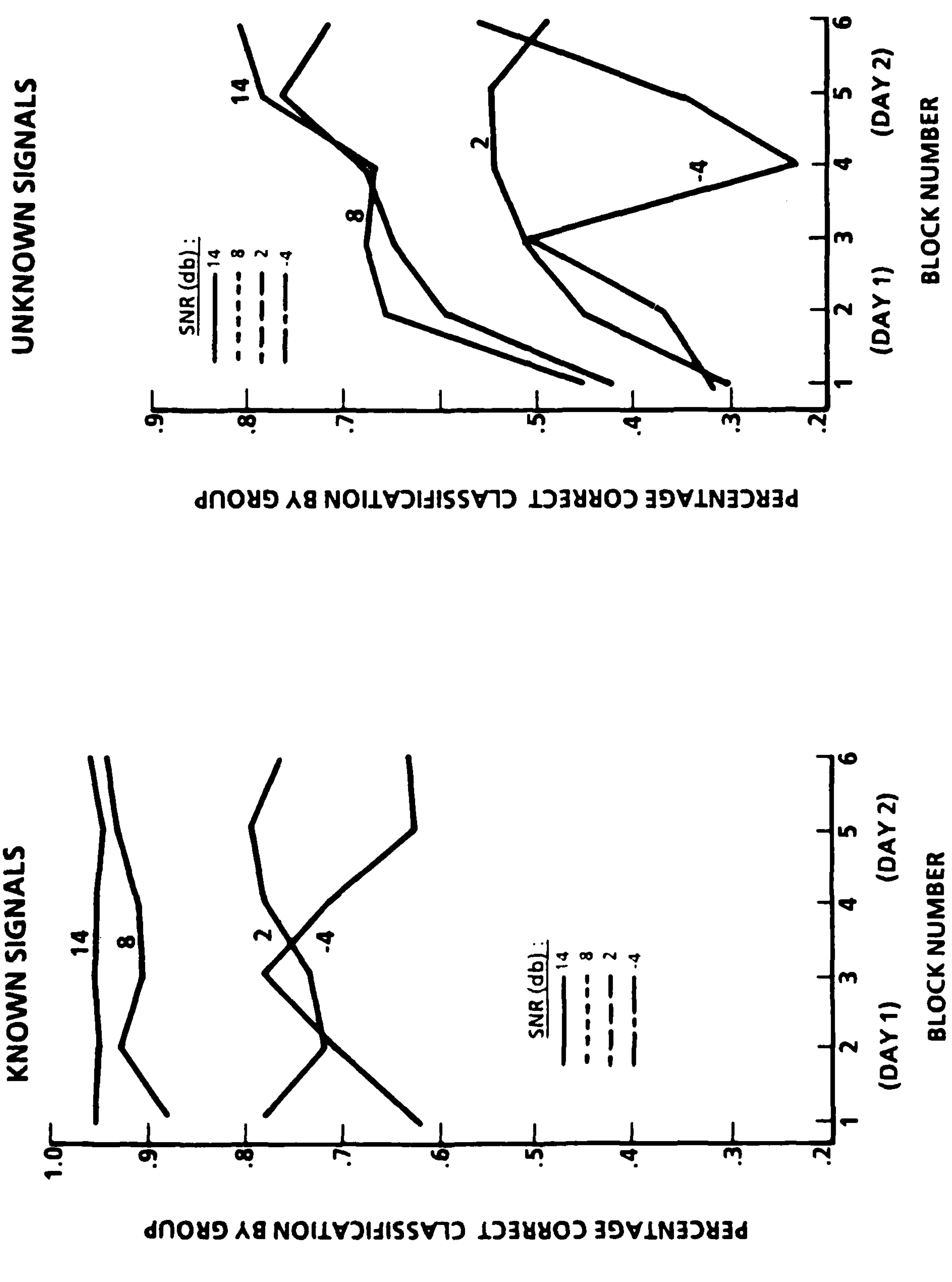

Figure 3-15. Classification Latency (Experiment 2)

For unknown signals, the percentage of correct classification by group increased over successive blocks during each day, indicating learning took place. However, between blocks 3 and 4, a drop in performance for -4 dB signals was found, indicating a loss of memory from the day before. Interestingly enough, in block 4, the -4 dB signals had classification performance less than chance responses. Like Experiment 1, the high SNRs and low SNRs were grouped separately, with the Experiment 2 classification performance being generally worse than that of Experiment 1.

Classification performance of known transients by signal type (Figure 3-16) was identical to that of Experiment 1, with the exception of the 2 dB signals having slightly worse performance. This result can also be attributed to the loss of the positional discriminant.

3.3.2.3 Response Latency Analysis

The latency time for classification was different from that of Experiment 1. To understand the reasons for this change, review of the cognitive and perceptual processes that occur during the experiment is necessary. The steps of detection and classification can be broken down into six notional processes:

1. Recognizing Signal. This step is an internal process which entails discovering clues which indicate a signal exists on the screen. One example of this includes finding "light worms" or unusual light patterns on the screen. For recognizing noise, the process entails either not finding any light worms, or

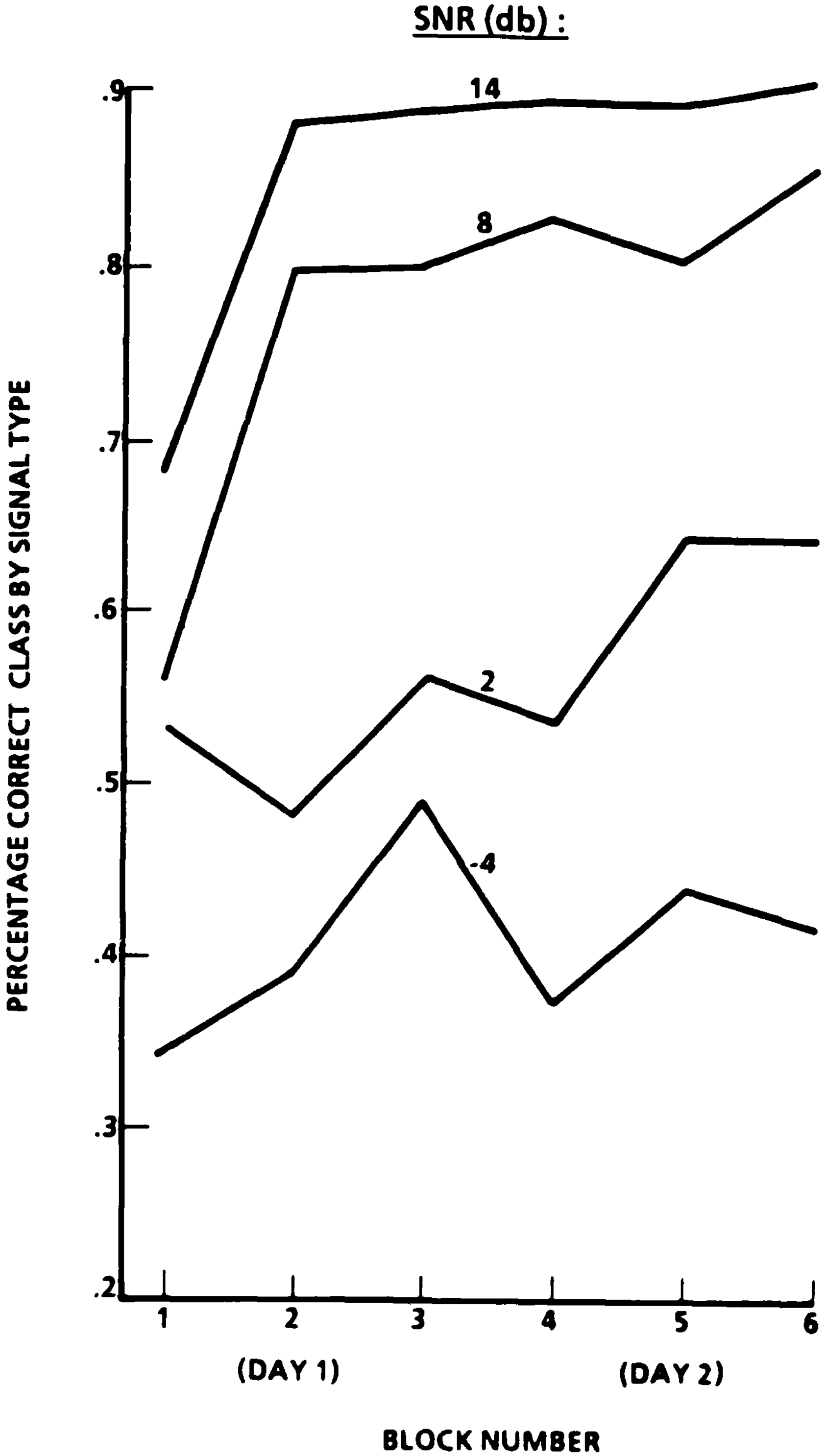

Figure 3-16. Classification Performance of Known Transients by Signal Type (Experiment 2)

seeing a uniform distribution of light on the screen. This is classical detection.

2. Deciding Whether Stimuli is Signal or Noise and With What Certainty. This step is an internal process which involves making the decision whether the stimuli is a signal or noise, and determining the degree of certainty associated with that decision.

3. Remembering the Detection Labels (1 - 4). This step is an internal process which involves remembering the number on the detection scale correlating to the decision made in (2) above.

4. Finding the Corresponding Detection Key. This step is an external process which involves finding on the keyboard the proper key that represents the desired response, and then pushing that key.

5. Classification of a signal can be accomplished in one of two fundamental ways:

   A. Feature/Pattern Queued Approach. This step is an internal process which involves matching stimulus patterns with transient patterns in one's memory. When no patterns in one's memory match the stimuli, stimuli is classified as a new signal. Following a match, the appropriate classification labels must be remembered.

   B. Label Driven Sequential Comparison. This step is an internal process which involves a step by step matching of the stimuli with each of the known signals. An example would be remembering signal A and trying to correlate it with the stimuli. If the correlation is unsuccessful, signal B is remembered and tried for correlation. It is important to note that when the correlation is made, the name of the signal is already known. If the stimuli is a new signal, the stimuli will not be classified as such until all of the known signals have been individually tried for correlation.

A clear and typical example of these two types of classification processes would involve a person, "Person 1," trying to identify a friend, "Person 2," from a distance. Classification process A is typified by Person 1 recognizing Person 2 but not knowing the person's name immediately. In this case, Person 1 has recognized specific feature characteristics of Person 2 but has not yet identified that person as "Bob." Classification process B is identified by Person 1 trying to decide which of his friends Person 2 is. The process by which Person 1 might identify Person 2 is by thinking of "Charlie" and then deciding whether there is a correlation between this person and Person 2. If no correlation exists, Person 1 might think of "John," and again try to make a correlation. This process would continue until "Bob" had been identified. Note that there is no apparent bias for either of the processes occurring in the experiment. In fact, there is no indication of any one of the processes being used exclusively.

6. Finding the Corresponding Key. This step is an external process which involves finding on the keyboard the proper key that represents the desired response, and then pushing that key.

If detection and classification were assumed to be independent of each other, steps 1 through 4 would always be separated from steps 5 and 6. However, the latency results of both Experiment 1 and Experiment 2 indicate some classification processing occurring during the detection phase of the experiment.

The latency of the participant to detect signals and noise (Figure 3-17) was slightly different from the results in Experiment 1. The differences are twofold. First, between block 3 and 4, the mean detection latency for the low SNRs increased, indicating a relapse in performance (from day to day) to differentiate quickly between noise and transients. It is noted, however, that the mean detection time does generally decrease with successive blocks, with block 6 showing the best results. Second, the mean detection time for 2 dB signals was consistently <u>less</u> than that of Experiment 1. The implications of this difference are tied to the above hypothesis concerning the classification performance threshold. Because the 2 dB signals are more difficult to classify correctly (Figure 3-15), one would expect the time spent trying to classify the signals to be greater (as shown in Figure 3-18), as well as the time spent trying to detect them. However, Figure 3-17 shows a decrease in the mean detection latency compared to Experiment 1. The decrease in the mean detection latency (2 db signals) between Experiments 1 and 2 indicates that there is a tendency for the participant to separate the detection from the classification in Experiment 2, thereby making detection faster and classification slower. Both Figure 3-17 and Figure 3-18 support this hypothesis.

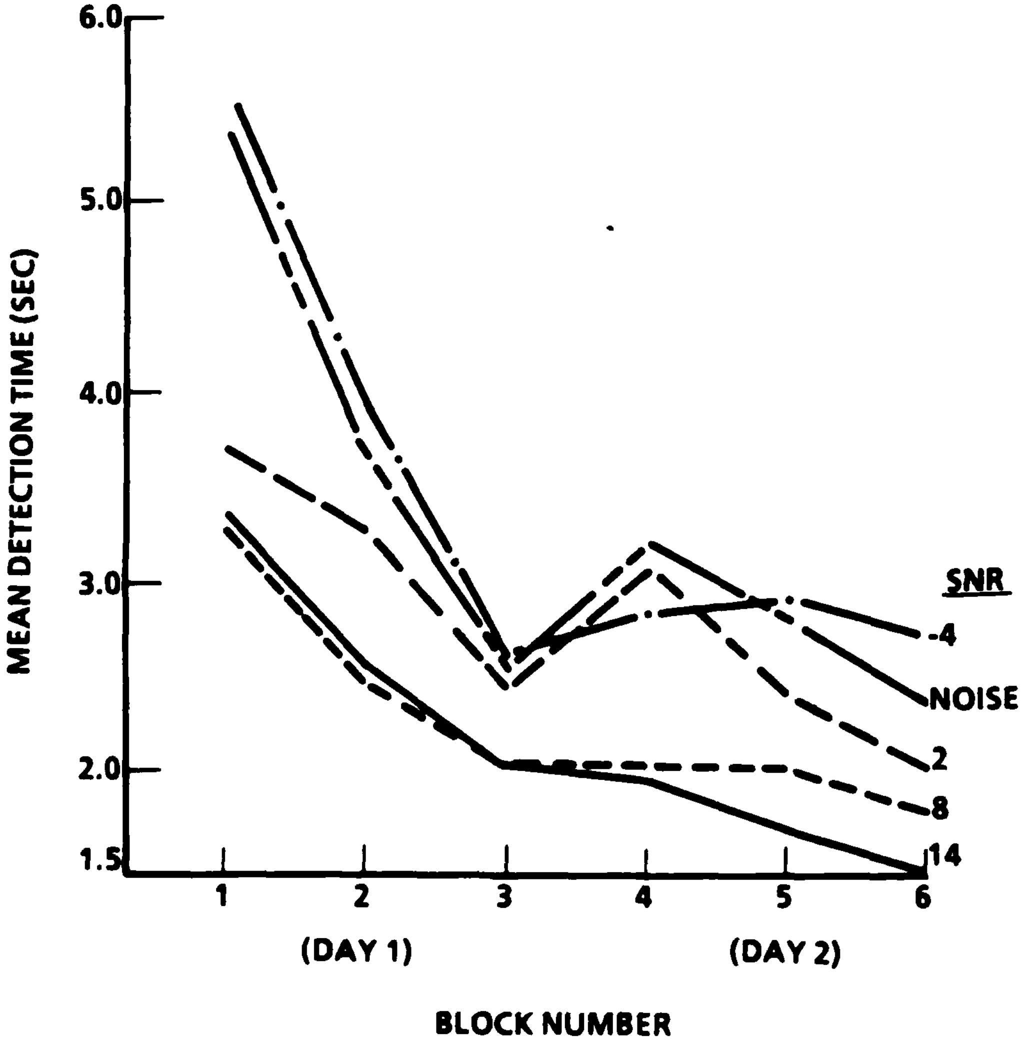

Figure 3-17. Comparison of Detection Latency for Signals and Noise (Experiment 2)

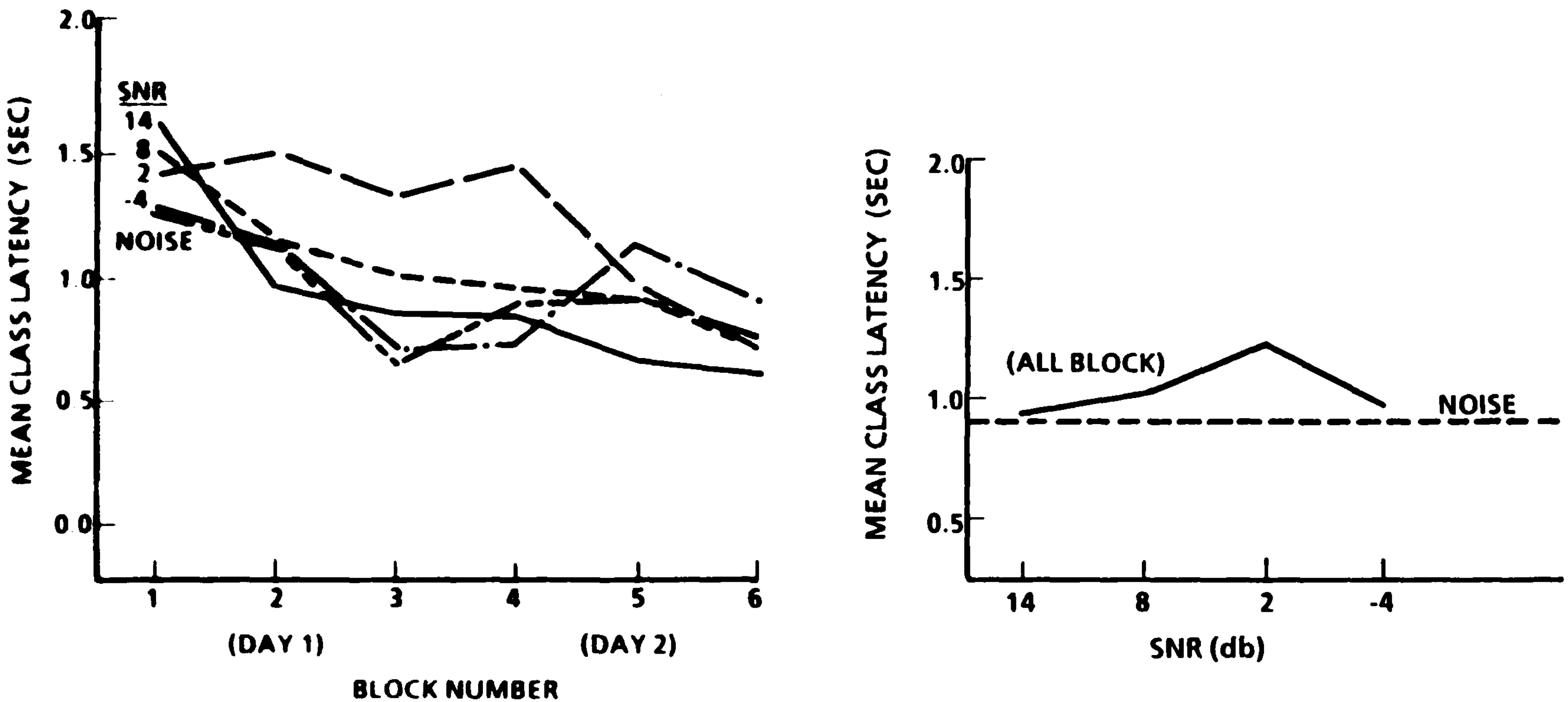

Figure 3-18. Classification Performance for Known and Unknown Signals by Group (Experiment 2)

The other difference in the mean detection latency data is that noise has greater values in comparison to Experiment 1. Note also that the mean classification latency of noise (Figure 3-18) dropped from 1.15 seconds in Experiment 1 to 0.85 second in Experiment 2. These data represent the other side of the classification latency issue. At some point, detection becomes so difficult that the participant is reluctant to answer positively to a detection until a certain amount of classification processing has taken place. This would imply that parts of step 5 (described above) would occur before step 2.

The same hypothesis can be applied to the detection and classification latencies for -4 dB signals. As is apparent in Figure 3-17, the -4 dB signals have a significantly greater latency for detection than the other SNRs. It is important to note that detection latency should increase with the decrease of SNR, simply because the signal is more difficult to see. However, the -4 dB signals have abnormally greater detection latencies, indicating additional internal processing. Likewise, Figure 3-18 illustrates the mean classification latency for -4 dB signals as being less than expected. Because more classification processing is occurring during the detection phase of the experiment, less time is necessary for classification during the classification phase.

3.4 GENERAL DISCUSSION

The analysis of Experiment 1 and Experiment 2 has lead to seven significant results:

1. Transient detection and classification performance are highly independent. Both are very sensitive to SNR.

2. Novices were able to rapidly detect and classify unknown transients, including those with significantly novel structure. This implies rapid and accurate internal representation and recognition of pure noise backgrounds and/or identification of replicated features different from the white Gaussian noise background.

3. The feedback given on known transients resulted in better performance at low SNR when compared to performance for unknown transients. This was in spite of repeated observation of the unknown transients at high SNR, and associated excellent performance.

4. Performance varied widely from transient to transient. This transient specific structure (syntax) effect was much stronger than the known vs. unknown group effect.

5. Novice detection performance against acoustic transients in the experiment was comparable to theoretical best operator detection of broadband signatures using conventional sensors. Experienced sonar operators outperformed the novices by 12 dB.

6. Human detection and classification decision-making are interrelated in fundamentally different ways for high and low SNR transient signals.

7. The variable positioning of transient signals in Experiment 2 caused decreased detection and classification performance, showing the participants' reliance on position related clues.

3.5 ATTACHMENT A: STUDENT INSTRUCTIONS AND POST-EXPERIMENT QUESTIONNAIRE

3.5.1 Instructions

The experiment you are about to start is a visual detection and identification task. You will be payed $5.00 per day for your participation in the experiment with a possible bonus of $2.00 per day added for good performance. Before you begin each block of trials you will have a preview session to familiarize yourself with the testing procedure and the target signals. The target signals will consist of patterns of bright patches in a background of a randomly specked display. You will examine three different target signals. Each signal displays its own unique pattern of bright patches on the video monitor. These three signals with different patterns are labelled A, B, or C. Try to remember each pattern and associate its designated label A, B, or C. During a preview session you will also examine three displays showing only the background and not containing any signal. These non-signals appear uniformly speckled without any bright patches indicating a signal pattern. I will guide you through the actual testing procedure during the first preview session.

Once the preview session is completed, a formal testing session will begin. During this testing you will be presented these same three signals (A, B, and C); some other new signals with different patterns; and some displays with no signals. The brightness of the signals will vary; blending in some cases into the speckled background. In some cases signal patterns will be easy to see; in other cases, very difficult to discern from the nonsignal speckled background. On each of these trials, you will be asked if a signal is present. You will respond by pushing the appropriate number key as (1: definitely no signal; 2: probably no signal; 3: probably a signal; 4: definitely a signal). If you respond with 3 or 4 (probably a signal or definitely a signal) you will be given an opportunity to identify which of the signals you think you are seeing. In those cases you will respond by pressing the appropriate letter (A: for signal A; B: for signal B; C: for signal C; and O: for other or new type of signal).

After you make your response, feedback will appear on the display. If, in truth, the trial consisted of a known target signal A, B, or C; then the appropriate letter (A, B, or C) will be displayed on the monitor. If, in truth, the trial consisted of a new type target signal or non-signal (no target present) then the character "?" will appear on the monitor. When you are ready to go on to the next trial, press the key labelled "continue".

After 96 test trials are completed, your screen will indicate that "block 1" is over. At that point, I will come in to answer any of your questions regarding the experimental procedure. You will then go on to "block 2." The procedure will consist of the same preview followed by 96 additional trials. After "block 2" is completed, a final "block 3" will be performed. Each block is expected to take 15 to 20 minutes; so the entire session will last about 1 hour. The second day of testing will proceed in a similar fashion to the first: three more blocks of previews followed by testing. At the end of the second day of testing, you will be asked to fill out a brief questionnaire describing your experience.

Your performance bonus will be based on your ability to detect and correctly intensify target signals. Remember some of the cases are extremely difficult--do not be discouraged--do the best you can.

3.5.2 POST EXPERIMENT QUESTIONNAIRE

1. Did you see the target signal every time it was there?

   Never 1 2 3 4 5 6 7 8 9 10 Always

2. Did you see any target signals when none were actually present?

   Rarely 1 2 3 4 5 6 7 8 9 10 Often

3. How did you decide that a target signal was present?

4. How well do you think you correctly identified the target signal?

   Type (A,B,C, & O)?

   Poorly 1 2 3 4 5 6 7 8 9 10 Extremely Well

5. How did you decide on the identity of the target signal?

6. Briefly describe target signal Type A:

7. Briefly describe target signal Type B:

8 Briefly describe target signal Type C:

9. Briefly describe any new (i.e. "other") target signal type(s) observed:

10. Briefly describe the speckled background:

11. How often did you use an internal (remembered) <u>verbal</u> description of the target signal to make decisions?

Never 1 2 3 4 5 6 7 8 9 10 Always

12. How often did you use internal (mental) pictures to make decisions

Never 1 2 3 4 5 6 7 8 9 10 Always

13. Please make any comments or suggestions:

THANK YOU FOR YOUR PARTICIPATION.

4.0 AUTOMATIC CLASSIFICATION RESEARCH

The purpose of this feasibility research is to test a computational theory of an Asynchronous Syntactic Pattern (ASP) sensor. Its purpose is to sense the physical features of transients in real time and to interpret complex sounds as serial sequences of pulse features, i.e., as syntax or as syntactic events. In this sense, the ASP sensor is a transducer of physical sensors, transforming their infinite sequentially sampled data to a finite set of transient features which repeat from time to time, forming a structured syntax with implicit meaning for human operators with classification objectives.

The patterns are represented top-down as a generic classifier system hierarchy. Different types of pulses are considered as independent entities. These entities broadly describe the transient in general terms. As one moves down the hierarchy, each generic entity is further described in terms of feature attributes. Moving further down the hierarchy, each feature attribute is described in terms of a vector of feature attribute values. This vector of feature attribute values is referred to as a feature pattern. At the bottom of the hierarchy is syntax. The simplest representation at this level are binary state variables representing time-ordered excitations and inhibitions of a feature pattern. More complex syntax, involving structured pattern sequences, i.e., a rule-based grammar, is handled at a higher level by creating a symbol for each syntax. At the bottom, it is either singular or a bit mapped time pattern, commonly known as a binary state variable. There are many advantages to this kind of transient representation, which is beyond the scope of this report.

At the top of our classifier system hierarchy, there are four discrete pulse entities. These are (1) leading edges, (2) correlated pulsed carriers, (3) singular pulsed carriers, and (4) aperiodic pulses. This selection is in no sense optimized, but nevertheless represents a rational beginning for the feasibility analysis. In simplest terms, leading ledge pulse trains are approximately step functions. They start by a jump in power which is maintained for a variable period and either fade or are abruptly turned off. Pulsed carriers are processes which are periodic within randomly accessible time windows, and which have at least three cycles of wave motion. Pulsed carriers may be arbitrarily frequency modulated, amplitude modulated, or time patterned. Correlated pulse carriers are entities encompassing one or more identical replications of a feature pattern. The replications may occur on any time scale, may be predictable periodic occurrences, or may be multipaths with few visible replications. On the time-scale of available data, singular pulsed carriers are those with no apparent replications. The apparent singularity of events may not be real; the strategy is to hold singular events long enough to exhaust the possibility of associating their feature pattern with known groups, with subgroups split off of known groups because of ambiguous identification, or with other singular events to form a new group. Aperiodic events are residual events which fail the test for a minimum number of cycles of wave motion. The implication is that these events are more critically damped. Many passive transient signals may fall in this category.

4.1 RESULTS OF AUTOMATIC CLASSIFICATION PROCESSING

The Asynchronous Syntactic Pattern (ASP) sensor algorithm was programmed in FORTRAN for the Cray computer in order to test its feasibility as an aid for computer assisted classification of acoustic transients. The data was run on the Naval Research Laboratory Cray computer. This data made it possible to make real progress in evaluating the feasibility of the ASP sensor as a transient classification tool.

The ASP algorithm starts at the top of the classifier hierarchy by first sensing leading edges by the character of the pulse at the beginning of such events. Six such events were detected in the first six seconds of data and these will be described in more detail later. If the leading edge discriminant is false, ASP senses impulsive transients with at least three cycles of wave motion, which are called pulsed carriers. All of the pulsed carriers detected in 6 seconds (about 50,000 data points) are shown on Table 4-1. The attributes of the table are record number, data point number, and four feature pattern attributes. Those are each pulse's amplitude, average frequency (normalized to one at sample rate /2), pulse shape (from 0, minimum phase to 1, maximum phase delay of peak energy of the pulse), and frequency shift (normalized average frequency difference between decadent back and ascendent front of the pulsed carrier; positive means rising carrier frequency). Table 4-1 shows that ASP reduced the raw data from about 50,000 data items to about 500 data items.

Feature attributes of pulse shape, frequency shift and average frequency are taken as highest ranking keys for automatic classification of pulsed carriers, i.e., for grouping identical feature patterns in a three-dimensional feature space. This was implemented by transforming the three columns of key features in Table 4-1 to an integer between 0 and 25, inclusively. In that way we converted the key discriminants into an alphabetic string for efficient sorting of events with similar feature patterns.

Table 4-1. Pulsed Carriers Feature Attribute Values
Measured By: ASP Sensor (Asynchronous Syntactic Pattern)

Record	Point	Pulse Shape	Frequency Shift	Average Frequency	Filename	File Extension	Amplitude
79	0226	.1786	-.1826	.2500	PC790226	BBA	7525
79	0597	.6970	.0957	.3333	PC790597	SQK	5547
79	1583	.6000	.0556	.4667	PC791583	POZ	3360
79	2261	.8333	.2000	.3333	PC792261	WWK	6619
79	2343	.7368	.0429	.3684	PC792343	TNO	5664
79	3293	.7222	.0154	.3889	PC793293	TMQ	5424
79	3477	.7500	.0667	.3500	PC793477	TPM	6864
79	3616	.6087	-.0952	.3913	PC793616	PGQ	7797
80	0084	.7391	.0392	.3043	PC800084	TNG	5616
80	0284	.6316	.0952	.3684	PC800284	QQO	5643
80	0508	.9259	.1400	.3704	PC800508	ZSO	4859
80	0650	.6250	.1000	.4375	PC800650	PQW	6160
80	1619	.2778	-.0154	.3889	PC801619	EKQ	6619
80	1876	.4000	-.0667	.3600	PC801876	IHN	6395
80	2195	.7368	.0429	.3684	PC802195	TNO	6800
80	2446	.5556	-.0250	.3889	PC802446	NKQ	6517
80	2498	.4444	.0250	.3889	PC802498	KMQ	7056
80	2683	.5926	.0511	.3333	PC802683	OOK	7211
80	2770	.7619	.0875	.3333	PC802770	UQL	6341
80	3035	.9167	.1364	.3750	PC803035	ZSO	4784
80	3197	.5556	-.0250	.3889	PC803197	NKQ	6315
80	4018	.6316	.0952	.3684	PC804018	QQO	6843
81	0643	.7000	.1429	.4000	PC810643	STR	8859
81	1098	.5556	-.0250	.3889	PC811098	NKQ	6640
81	2137	.5556	-.0250	.3889	PC812137	NKQ	7515
81	2958	.5000	.0000	.3333	PC812958	LLK	6176
81	3992	.6500	-.0989	.3500	PC813992	QFM	5397
82	0242	.2083	-.0316	.3750	PC820242	CJO	6736
82	0967	.2381	-.0875	.3333	PC820967	DGK	6197
82	1442	.6667	.1429	.3333	PC821442	RTK	6117
82	1902	.4500	.0303	.3500	PC821902	KNM	7664

Table 4.1 (Cont)

Record	Point	Pulse Shape	Frequency Shift	Average Frequency	Filename	File Extension	Amplitude
82	2680	.1429	.0000	.3333	PC822680	ALK	7467
82	2993	.1500	.0196	.3500	PC822993	AMM	6219
83	4319	.2273	-.0471	.3636	PC831319	DIN	5147
83	1920	.5000	-.1000	.3500	PC831920	LFM	5397
83	2274	.7273	-.0417	.3636	PC832274	TJN	3072
83	2302	.4444	.0250	.3889	PC832302	KMQ	6069
83	2653	.7391	-.0196	.3478	PC832653	TKL	6427
83	3356	.6842	-.0513	.3684	PC833356	RIO	7387
83	3775	.5263	-.0667	.3684	PC833775	MHO	10581
83	4094	.6500	.1209	.3500	PC834094	QPM	5291
84	1771	.3500	-.1209	.3500	PC841771	HEM	6853
84	1838	.3478	.0833	.3043	PC841838	HPG	6459
84	1969	.5833	.0143	.2917	PC841969	OMF	6432
84	2519	.8889	.1250	.3889	PC842519	YSQ	5856
84	2600	.5789	.0114	.3684	PC842600	OLO	6880
86	1026	.6875	-.0545	.4375	PC861026	RIW	6896
86	1227	.4118	-.0286	.4118	PC861227	JJT	11227
86	1503	.5000	-.1250	.4375	PC861503	LEW	11211
86	1626	.6111	-.2000	.3889	PC861626	PAQ	10976
86	1709	.5000	-.1000	.4375	PC861709	LFW	8848
86	2134	.4444	-.2000	.3889	PC852134	KAQ	10005
86	2805	.3750	-.1000	.4375	PC862805	HFW	7440
86	3449	.3750	-.1000	.4375	PC863449	HFW	6368
86	3670	.4444	-.2000	.3889	PC863670	KAQ	5147
86	3825	.3889	-.0649	.3889	PC863825	IHP	5552
87	0049	.3750	-.1000	.4375	PC870049	HFW	8912
87	0122	.3750	-.1000	.4375	PC870122	HFW	6992
87	0806	.5294	-.0694	.4118	PC870806	MHT	7813
87	0851	.5000	-.1250	.4375	PC870851	LEW	9557
87	1164	.5789	.0114	.3684	PC871164	OLO	6549
87	1689	.5000	-.1538	.3846	PC871689	LDQ	5957
87	2096	.6111	-.1688	.3889	PC872096	PCQ	7136
87	2621	.2500	-.0833	.4375	PC872621	DGW	5637

Table 4.1 (Cont)

Record	Point	Pulse Shape	Frequency Shift	Average Frequency	Filename	File Extension	Amplitude
87	3708	.4000	-.0556	.4667	PC873708	IIZ	8037
88	2414	.3750	-.1000	.4375	PC882414	HFW	9984
88	3224	.3333	-.1667	.3889	PC883224	GCQ	6848
89	1072	.2000	-.0625	.4500	PC891072	CHX	10288
89	1301	.6111	.0649	.3889	PC891301	POQ	10816
89	2327	.5333	-.0714	.4667	PC892327	NHZ	7984
89	3153	.3889	.0260	.4444	PC893153	IMX	6256
89	3524	.2500	-.0833	.4375	PC893524	DGW	7611
90	0749	.4000	-.1667	.4000	PC900749	ICR	4949
90	1024	.4375	.0159	.4375	PC901024	JMW	4496
90	1245	.4286	.0000	.3333	PC901245	JLK	5173
90	2512	.7391	.0392	.3043	PC902512	TNG	5328
90	3284	.4444	-.1000	.4444	PC903284	KFX	5099
90	3596	.3810	-.0673	.3333	PC903596	IHK	8997
91	1298	.2778	.2615	.3889	PC911298	EZQ	6123
91	1707	.5789	.0114	.3684	PC911707	OLO	5979
91	1833	.5000	-.0667	.2333	PC911833	LHA	4267
91	3329	.6000	.0333	.2800	PC913329	PND	5760
91	3460	.4545	-.0667	.3636	PC913460	KHN	4512
92	1073	.4583	-.0559	.3333	PC921073	KIK	7360
92	1742	.7895	.1667	.3684	PC921742	VUO	5312
92	1803	.6667	.1667	.3889	PC921803	RUQ	3125
92	1901	.4800	.0577	.2800	PC921901	LOD	6331
92	2719	.2917	.0084	.2917	PC922719	FLF	7387

Table 4-2. Pulsed Carriers Sorted by Feature Pattern

SORTED DIRECTORY: EXTENSIONS ARE KEY FEATURE ATTRIBUTES FOR CLASSIFICATION

FILENAME AND EXTENSION FORMAT: PCxxxyyyy.PSF

P: pulse shape S: frequency shift F: average frequency

(Feature attributes P, S, AND F transformed to range 0 to 25 for alphabet character representation in file extension sort keys)

(The content of the file: arrival time in seconds of the pulse)

PC: pulsed carrier xxx: record # yyyy: timedate #

```
.ALK files:     pc822680
.AMM files:     pc822993
.BBA files:     pc790226
.CHX files:     pc891072
.CJO files:     pc820242
.DGK files:     pc820967
.DGW files:     pc872621   pc893524
.DIN files:     pc831319
.EKO files:     pc801619
.EZO files:     pc911298
.FLF files:     pc922719
.GCO files:     pc883224
.HEM files:     pc841771
.HFW files:     pc862805   pc863449   pc870049   pc870122   pc882414
.HFG files:     pc841838
.ICR files:     pc900749
.IHK files:     pc903596
.IHN files:     pc801876
.IHP files:     pc863825
.IIZ files:     pc873708
.IMX files:     pc893153
.JJT files:     pc861227
.JLK files:     pc901245
.JMW files:     pc901024
.KAO files:     pc863670
.KAQ files:     pc862134
.KFX files:     pc903284
.KHN files:     pc913460
.KIK files:     pc921073
```

Table 4-2 (Cont)

.KMQ files:	pc802498	pc822702		
.KNM files:	pc821902			
.LDQ files:	pc871689			
.LEW files:	pc870851			
.LFM files:	pc871920			
.LFW files:	pc861507	pc861709		
.LHA files:	pc911877			
.LLP files:	pc812958			
.LOD files:	pc921901			
.MHO files:	pc877775			
.MHT files:	pc870806			
.NHZ files:	pc892327			
.NPQ files:	pc802446	pc803197	pc811098	pc812137
.OLO files:	pc842600	pc871164	pc911707	
.OMF files:	pc841969			
.OOP files:	pc802683			
.FAQ files:	pc861626			
.FCQ files:	pc872096			
.FGQ files:	pc793616			
.FND files:	pc913329			
.FOQ files:	pc891301			
.FOZ files:	pc791583			
.FQW files:	pc800650			
.QFM files:	pc813992			
.QFM files:	pc834094			
.QQO files:	pc800284	pc804018		
.RIO files:	pc833356			
.RIW files:	pc861026			
.RTP files:	pc821442			
.RUQ files:	pc921803			
.SOP files:	pc790597			
.STR files:	pc810643			
.TJN files:	pc832274			
.TKL files:	pc832653			
.TMQ files:	pc793293			
.TNG files:	pc800084	pc902512		
.TNO files:	pc792343	pc802195		
.TPM files:	pc793477			
.UQL files:	pc802770			
.VUO files:	pc921742			
.WWK files:	pc792261			
.YSQ files:	pc842519			
.ZSO files:	pc800508	pc803035		

Table 4-3. Multiple Arrival Time Pattern of Correlated Pulsed Carriers

MULTIPLE ARRIVAL TIMES OF IDENTICAL FEATURE PATTERN

FEATURE PATTERN	TIME (SEC) (From start of file)				
DGW	4.423625	5.5605			
HFW	3.934625	4.015125	4.102125	4.11125	4.90975
KMQ	0.82425	2.33575			
LFW	3.771875	3.797625			
NKQ	0.81775	0.911625	1.16125	1.291125	
OLO	2.885	4.2415	6.358625		
QQO	0.5475	1.01425			
TNG	0.5225	5.94725			
TNO	0.292875	0.785375			
ZSO	0.5755	0.891375			

sonar, pumps, engines, propeller cavitation, and other cyclical processes.

An important feasibility result of this research is the possibility of using a transient feature sensor to resolve intermittently sensed interfering harmonic beat patterns. This may have important practical significance complementing more conventional spectral techniques, to be discussed later. One obvious implication is the much lower recognition differential, as compared with a conventional power detector. The essential difference is that features can be sensed intermittently anytime that the feature is dominant with respect to other interfering stimulus. Once it is sensed, it can be recognized from replicative measurement of its feature attributes.

In order to determine how the selected feature classification keys are distributed, i.e., whether uniformly distributed over their range or concentrated, we prepared Table 4-4. The pulse shape shows some concentration between H and T, with some small bimodality at D. The Frequency Shift shows concentration between F and Q. Frequency is multimodal with concentrations at K, M, O, Q, and W.

The two principal classification keys are pulse shape and frequency shift. These features were selected as keys in the order considered most invariant with respect to the scale of source strength and propagations and also, on the physical grounds of being independent features. To test this idea, we plotted in Figure 4-1 occurrences of scaled (P, S) values in feature space. In the range of feature space where these attributes are concentrated, they appear to be random and uniformly distributed, i.e., not functionally related.

Table 4-4. Single Discrete Arrivals of Patterns (Multiple Arrivals Not Counted)

NUMBER OF OCCURRENCES OF FEATURE PATTERNS			
PULSE SHAPE	FREQUENCY SHIFT	AVERAGE FREQUENCY	PATTERN (SCALED)
2	3	2	A
1	1	0	B
2	3	0	C
4	1	2	D
2	2	0	E
1	5	2	F
1	3	2	G
3	9	0	H
6	6	0	I
3	3	0	J
7	3	10	K
7	5	2	L
2	6	7	M
2	4	4	N
3	4	9	O
7	3	1	P
3	4	14	Q
4	0	3	R
2	2	0	S
6	2	2	T
1	2	0	U
1	0	0	V
1	1	7	W
0	0	3	X
1	0	0	Y
1	1	3	Z

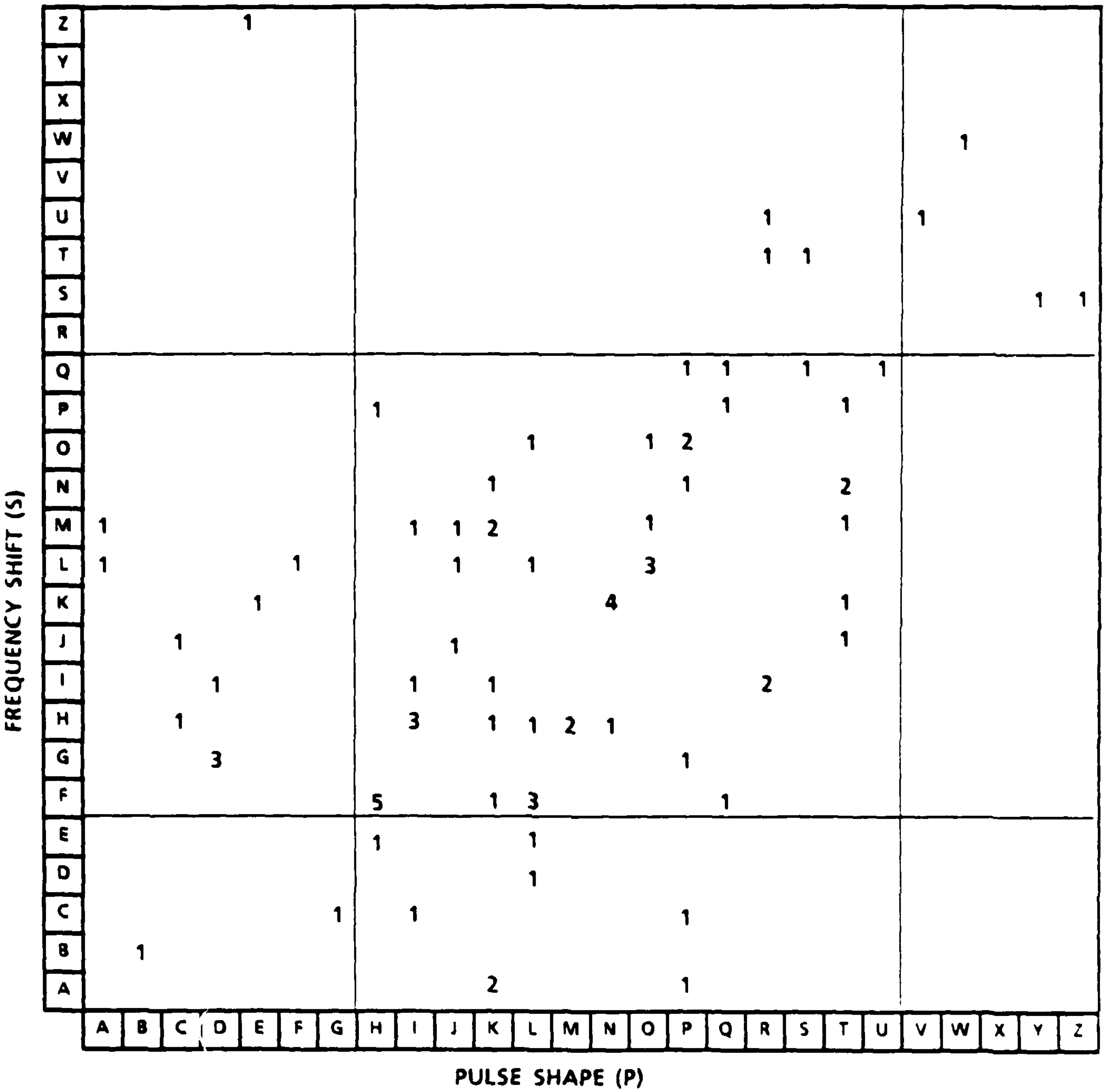

Figure 4-1. Relationship Between Frequency Shift and Pulse Shape

Multiple correlations obtained using these two features are shown as numbers greater than one in Figure 4-1. No obvious relationship or modality can be seen, although there is not enough data to be sure one way or the other. What can be seen is that there are 33 correlated pulses using P and S as keys. This is compared to 26 correlated pulses, using three features in the order P (Pulse Shape), S (Frequency Shift), and F (Average Frequency) as feature correlation keys, shown in Tables 4-2 and 4-3.

This means that adding Frequency as a feature removed about 20% of the (P, S) correlations as possible errors, suggesting an approximately 80% correlation of the (P, S) feature and actual (from targets) correlated pulses. Absolute interpretation of (P, S, F) actual correlated pulses is not possible to estimate without a priori knowledge. It is expected to be correlated more closely with actual pulses than is the lower ranking (P, S) feature pattern; especially considering the plus or minus 2% tolerance required for associating the frequency feature to two or more pulses (covering approximately one half octave of frequency band). Based on the (P, F) feature sense correlated pulses, there were 36 apparent correlations; on (S, F), 38 apparent correlations.

One important aspect of adding features is that additional pulses are missed and true correlations are fragmented, in exchange for much lower probability of falsely associating pulses. For that reason, care must be taken in expanding the dimension of feature space; in carefully setting the sensitivity of features; and rank ordering their application as key attributes of correlated pulses. The features used in this feasibility study must be optimized based on empirical analysis of a larger data base.

On detecting a set of correlated pulse carriers, other information is obtained which relates to a consistent interpretation of correlated pulses. Important to the identification harmonic patterns are the sequence of arrival times observed and associated with a feature pattern; to the identification of multipath arrivals time delays consistent with ocean depth and range. Amplitude information, as shown in Table 4-1, is obtained with each correlated pulse. Amplitude can be used to gauge the source or propagation distance, given appropriate environmental modeling.

4.2 INTERPRETATION OF CORRELATED PULSE CARRIERS

We have demonstrated that an Asynchronous Syntactic Pattern (ASP) sensor can efficiently reduce acoustic data to long leading edge transients, modulated narrowband pulsed carriers, and broadband transients. One interesting observat[illegible] made with the pulsed carriers was that their random occurrences could be easily sensed as transients at much lower amplitude levels than the transients used in the Psychophysical Exper[illegible] ment, i.e., at levels 15.5 dB less than those used in the experiment. This was possible because the transients [illegible] tinguished, not in the usual sense of sudden large am[illegible] but on the basis of features similar to those used [illegible] classificaiton. These were pulse shape, measuremen[illegible] time relative to duration of the transient; fre[illegible] measurement of chirp characteristic frequen[illegible] quency of the carrier.

The only requirement for identifying [illegible] feature patterns is that the wavef[illegible] occasionally dominate a few dB [illegible] is possible because the measurem[illegible]

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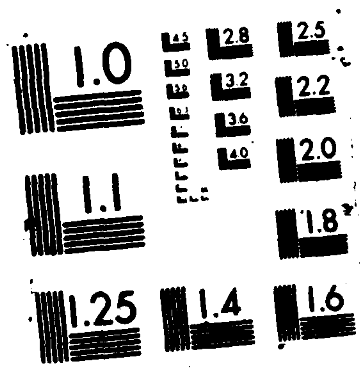
1.0
2.8
2.5
3.2
2.2
3.6
4.0
2.0
1.1
1.8
1.25
1.4
1.6

designed to be measured effectively at emergent peak values and at very low recognition differentials. Alternatively, coherent stacking may be used to pull the transient out of the noise. Those feature patterns which replicate very precisely can be used to identify and very precisely measure source characteristics.

The algorithm for carrying out this experiment of feature correlation was performed as part of the Cray Processing. It simply consisted of a linear stack holding the last 16 pulse carriers. If a new correlated pulse gets pushed onto the stack soon enough, it will correlate based on the near identity of the three measured features. This is accomplished on a three by sixteen element stack. The frequency and frequency shift criteria was set at 2%; the pulse shape at 5%. Twenty-two correlations obtained by the Cray Experiment are shown on Table 4-5. One immediately takes note of the dominance of two different pulsed carrier wave trains. The only exception was the correlated pair on record 87 point 1164. Its feature pattern is well separated from the two pulse trains. With a time delay of 1.3 seconds and an apparent reflection coefficient of 0.95, it could conceivably be a multipath event.

The pulse carrier wave trains were further analyzed to see if some information about the source could be obtained. This was done by determining the extent that the pulse train is periodic, and therefore indicative of a harmonic pattern emitted from the source. By dividing one of the time intervals by an integer and taking that value as a prediction time period between pulses, the repeat time was tested by division into each of the observed time delays. This was repeated by trial and error until numbers very close to integers were obtained for

Table 4-5. Correlated Pulse Carriers by Real-Time Stacked Feature Correlation

RECORD	POINT	REPEAT TIME	AMPLITUDE	AVERAGE FREQNCY	PULSE SHAPE	FREQNCY SHIFT
83	1920	0.0000	5397.	0.3500	0.5000	-0.1000
		0.7340	5397.	0.3500	0.6500	-0.0989
86	1709	0.0000	8848.	0.4375	0.5000	-0.1250
		0.0247	11211.	0.4375	0.5000	-0.1250
86	3449	0.0000	6368.	0.4375	0.3750	-0.1000
		0.0773	7440.	0.4375	0.3750	-0.1000
87	49	0.0000	8912.	0.4375	0.3750	-0.1000
		0.0835	6368.	0.4375	0.3750	-0.1000
		0.1608	7440.	0.4375	0.3750	-0.1000
87	122	0.0000	6992.	0.4375	0.3750	-0.1000
		0.0088	8912.	0.4375	0.3750	-0.1000
		0.0923	6368.	0.4375	0.3750	-0.1000
		0.1696	7440.	0.4375	0.3750	-0.1000
87	851	0.0000	9557.	0.4375	0.5000	-0.1250
		0.3886	8848.	0.4375	0.5000	-0.1250
		0.4133	11211.	0.4375	0.5000	-0.1250
87	1164	0.0000	6549.	0.3684	0.5789	0.0114
		1.3022	6880.	0.3684	0.5789	0.0114
88	2414	0.0000	9984.	0.4375	0.3750	-0.1000
		0.7753	8912.	0.4375	0.3750	-0.1000
		0.9361	7440.	0.4375	0.3750	-0.1000
89	3524	0.0000	7611.	0.4375	0.2500	-0.08332
		1.0914	5637.	0.4375	0.2500	-0.0833
26	3058	0.0000	6923.	0.3889	0.5556	-0.0250
		0.0416	5936.	0.3889	0.5556	-0.0250
80	3197	0.0000	6315.	0.3889	0.5556	-0.0250
		0.0901	6517.	0.3889	0.5556	-0.0250
81	1098	0.0000	6640.	0.3889	0.5556	-0.0250
		0.2396	6315.	0.3889	0.5556	-0.0250
		0.3298	6517.	0.3889	0.5556	-0.0250
81	2137	0.0000	7515.	0.3889	0.5556	-0.0250
		0.1247	6640.	0.3889	0.5556	-0.0250
		0.3643	6315.	0.3889	0.5556	-0.0250
		0.4544	6517.	0.3887	0.5556	-0.0250
150	2283	0.0000	3205.	0.3889	0.5556	-0.0250
		0.9024	3659.	0.3889	0.5556	-0.0250

each observed repeat time differential. A basic program for performing this analysis is given in Figure 4-2.

The result obtained in predictive timing of correlated pulsed carriers is shown in Table 4-6. Referring back to Table 4-3 showing multiple arrival times, we note the close similarity of HFW and LFW. The matrix of feature correlated time differentials indicated that the predicted arrival times of HFW and LFW were on the same wave train. This amounted to a total of 12 correlated time differentials over a period of about 2.5 seconds. The other pattern, NKQ, was approximately 6 dB weaker and occurred more sporadically than HFW. It was sensed only 8 times; 6 times over a period of one second, but only 8 times over the entire observation period of about one minute.

The repetition time of the HFW pulsed carrier is 3.0884 msec; of the NKQ pulsed carrier, 3.4693 msec. The standard deviation of pulse timing errors is .05 of the repetition time for NKQ; .106 for HFW. The apparent precision of a pulse train model for correlating pulses is .2 to .4 msec. The average period of NKQ is .643 msec; of HFW, .571 msec. The possibility of estimating pulsed carriers by a repetition time delayed waveform stack or by matched filtering is not beyond reasonable bounds.

4.3 INTERPRETATION OF LEADING EDGE TRANSIENTS

The leading edge transient detections were the type of transients used in the Pilot Psychophysical Experiement. They were the largest transients on the NSWC tape; on an average 15 dB larger than the pulsed carriers described in the preceding section. We used them as examples of extremely long (about 0.1 to 1.0 second) transient episodes. By contrast, the pulsed

```
1 '------NAME:  "FULSENUM" ------------------------------
3 'J = INTGR FRAC OF F (1)    F(I) ORDERED SMALLEST TO LARGEST
4 'PERIOD DIVSR MAKES G(I) INTEGER: REPEAT IS REFINEMENT TRIAL & ERROR
5 DIM F(64), G(64)
10 INPUT N
20 FOR  I = 1 TO N
25      INPUT F(I)
30 NEXT I
33      INPUT J
35      IF J = 0 THEN GOTO 70
37 PERIOD = F(1)/J  : PRINT J,PERIOD
40 FOR I = 1 TO N
45      G(I) = F(I)/PERIOD : PRINT G(I)
50 NEXT I
60 GOTO 33
70      INPUT SCALE : REPEAT = PERIOD * SCALE : PRINT PERIOD:SCALE.REPEAT
75      IF SCALE = 0 THEN GOTO 33
80 FOR I = 1 TO N
85      G(I) = F(I)/REPEAT : PRINT F(I),G(I)
90 NEXT I
95 GOTO 70
99 END
```

Figure 4-2. Basic Program to Calculate Period of Repetition for Intermittent Correlated Pulses

Table 4-6. Analysis of Feature Correlated Pulsed Peak Delay Time Differentials

PULSED CARRIER PEAK TIME DIFFERENTIALS

NKQ: Estimated Repetition Time = 3.4693 Msec

Time Differential	Peaks Differential
.0416 sec	11.99
.0901	25.97
.1247	35.94
.2396	69.06
.3298	95.06
.3643	105.01
.4544	130.98
.9024	260.11

HFW & LFW: Estimated Repetition Time = 3.0884 Msec

Time Differential	Peaks Differential
.0088 (round off error)	2.85
.0247*	8.00
.0773	25.03
.0835	27.04
.0923	29.89
.1608	52.07
.1696	54.91
.3886	125.82
.4133*	133.82
.7753	251.03
.9361	303.10

carriers were about 2 msec entities. We observed 6 of these signals over a time period of about 2 minutes.

The experiment with Leading Edge transients consisted of sensing the front edge of the signals with a step function; and measuring the features of the front edge of the signal. These are shown for the six signals in Table 4-7. The leading edge feature values indicate that event 3 and 4 are closely correlated based on pulse shape, frequency shift and amplitude. They are not well correlated with frequency.

An important part of the experiment was concerned with the 512 nodal binary state variable of energy excitation. We were interested in this as a very computationally efficient and simple syntax for very long complicated signals. The sensitivity in correlating signals 3 and 4 from the binary state variable was remarkable, as seen in the binary correlation matrix in Table 4-6. The correlation is 100% in terms of bit masking of event 4 on 3. The result is slightly complicated by the fact that event 3 has 12% more bits than event 4. The typical correlation between patterns nearly matched in number of bits is between .3 and .6. The precise binary state variable pattern match between 3 and 4 is based on nearly the same time span with signal certainty uniformly turned on. One interesting fact is the apparent consistency between feature patterns of events 3 and 4 based on pulse shape, frequency shift and amplitude measurements of the leading edge, and the bit mapped long complex signal. One is lead to speculate that event 3 and event 4 are similar entities.

Table 4-7. Leading Edge Transient Feature Pattern and Binary State Variable of Energy Activation

N	RECORD	POINT	AMPLITUDE	AVERAGE FREQNCY	PULSE SHAPE	FREQNCY SHIFT
1	53	2882	16613.	0.2381	0.3810	-0.0192
2	119	177	7627.	0.1250	0.9062	0.2299
3	130	1905	32325.	0.3437	0.0625	-0.1667
4	135	1296	32752.	0.1765	0.0882	-0.1720
5	160	1634	9349.	0.1667	0.6667	0.1250
6	306	2148	29061.	0.1351	0.8919	0.4091

N	ENERGY ACTIVATION SENSORY STATE VARIABLE
1	80808080C681C000E03EE007F8000000FE006FFDFE00013FFFE00400000000000 FFFC800A3DFFFFFBFFFE4000402B1FFFFFFFFDA48130202000000000000000000
2	80000000002000000009C0000000000000400000000EBF204000000000000 3A54000000000016FEDFFF6DA4B2012082000000000000000000000004000010
3	A8C0F000FF800000FFFFC00000000000FFFFFFFFF00000000000000000000000 FFFFFFFFFFFFFFFFFF2000000000000000000000000000000000000000000000
4	88C0F000FF000000FFFF000000000000FFFFFFFF000000000000000000000000 FFFFFFFFFFFFFFFF4000000000000000000000000000000000000000000000000
5	8000800081602000E0A77E401D822000FC01EDBFBFFE300003F7C49E4D800000 FFF00117FDF7EFFFDFFFFFFFD5FA0000015FFFBFF9B6DBFDB6FBE8200000000
6	8000000080000000C000000000000000E0000000000000000000000000000000 FA00000000000000000000000000000000000000000000000000000000000000

BINARY CORRELATIONS

	1	2	3	4	5	6
1	188	37	96	81	120	13
2	37	69	23	13	54	6
3	96	23	145	129	90	13
4	81	13	129	129	79	13
5	120	54	90	79	234	13
6	13	6	13	13	13	13

4.4 CONCLUSIONS

This preliminary examination of data, indicates that our theory of an Asynchronous Syntactic Pattern (ASP) sensor is potentially capable of reducing synchronous data by at least a factor of 100. This is assuming that all of the singular feature patterns would be retained and processed. Given the requirement of interactive processing of only correlated events; and the feasibility of machine correlating patterns and syntax by our algorithm, the reduction factor of data storage and processing is of the order of 500. Beyond computational feasibility and data reduction possibilities, we have shown that useful information about the source can be obtained and conveyed to the human classifier. An automatic transient processor with empirical AI and self-learning capabilities will probably be essential in meeting future combat requirements of accurate classification and rapid human response. It is interesting to note that two long complex transient episodes were highly correlated on the basis of a bit mapped syntactic state variable, and independently on the basis of a feature space representation only operating on the leading edge of the long transient. Pulse shape and frequency agreed within a tolerance of 3%; and amplitude agreed within a tolerance of 1%. The bit mapped energy excitation masked 100%.

In pushing ahead with ASP, we plan to implement a neural network model for the purpose of recognizing noisy syntax patterns, for self-learning of new patterns, and for automatic recall. Automatic recall could be used for recognizing hybrid patterns obtained by appending the binary state variable with human generated form entries. We should continue exploring the capabilities of feature attributes as a front-end hierarchical feature sensor. In particular, we should continue to explore in depth the extraction of additional useful information about the source.

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